Stock Return Asymmetry: Beyond Skewness*

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Abstract

In this paper, we propose two asymmetry measures of stock returns. In contrast to the usual skewness measure, ours are based on the distribution function of the data instead of just the third moment. While it is inconclusive with the skewness, we find that, with our new measures, greater upside asymmetries imply lower average returns in the cross section of stocks, which is consistent with theoretical models such as those proposed by Barberis and Huang (2008) and Han and Hirshleifer (2015).

Keywords Stock return asymmetry, entropy, asset pricing

JEL Classification: G11, G17, G12

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1. Introduction

Theoretically, Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2008), and Han and Hirshleifer (2015) show that a greater upside asymmetry is associated with a lower expected return. Empirically, using skewness, the most popular measure of asymmetry, Harvey and Siddique (2000), Zhang (2005), Smith (2007), Boyer, Mitton, and Vorkink (2010), and Kumar (2009) find empirical evidence supporting the theory. However, Bali, Cakici, and Whitelaw (2011) find that skewness is not statistically significant in explaining the expected returns in a more general set-up. Overall, the evidence on the ability of skewness as a measure of asymmetry, is mixed and inconclusive in explaining the cross section of stock returns.

In this paper, we propose two distribution-based measures of asymmetry. Intuitively, asymmetry reflects a characteristic of the entire distribution. Since skewness concerns only the third moment, it does not measure asymmetry induced by all the other moments. Therefore, even if the empirical evidence on skewness is inconclusive in explaining asset returns, it does not mean asymmetry does not matter. Clearly, this comes down to how we better measure asymmetry. Our first measure of asymmetry is a simple one, defined as the difference between the upside probability and downside probability. This captures the degree of upside asymmetry based on probabilities. The greater the measure, the greater the upside potential of the asset return. Our second measure is a modified entropy measure originally introduced by Racine and Maasoumi (2007) who assess asymmetry by using an integrated density difference.

Statistically, we show via simulations that our distribution-based asymmetry measures can capture asymmetry more accurately than skewness. Moreover, they can serve as symmetry tests of asset returns with higher power. For example, for value-weighted decile size portfolios, a skewness test will not find any asymmetry except for the smallest decile, while our measures detect more.

Empirically, we examine both skewness and our new measures for their explanatory power in the cross-section of stock returns. We conduct our analysis with two approaches. In the first approach, we study their performances in explaining returns by using Fama and MacBeth (1973) regressions. Based on data from January 1962 to December 2013, we find that there is no apparent relationship between the skewness and the cross-sectional average returns. This is consistent with the findings of Bali et al. (2011). In contrast, based on our new measures, we find that asymmetry does matter in explaining the cross-sectional variation of stock returns. The greater the upside asymmetry, the lower the average returns in the cross-section.

In the second approach, we sort stocks into decile portfolios of high and low asymmetry with respect to skewness and to our new asymmetry measures, respectively. We find that while high skewness portfolios do not necessarily imply low returns, high upside asymmetries based on our measures are associated with low returns. Overall, we find that our measures explain the asymmetry sorted returns well, while skewness does not.

Our empirical findings support the theoretical predictions of Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2008), and Han and Hirshleifer (2015). In particular, under certain behavior preferences, Barberis and Huang (2008) show that it is tail asymmetry and not skewness proxy that matters for expected returns.[1] Without their inherent behavior preferences, Han and Hirshleifer (2015) show via a self-enhancing transmission bias (i.e., investors are more likely to tell their friends about their winning picks instead of losing stocks) that investors favor the adoption of investment products or

[1]While their paper focuses on skewness, their proof, equation (33), in fact indicates that it is the asymmetric payoff of the assets that matters.

strategies that produce a higher probability of large gains as opposed to large losses. Again this is more on asymmetry than on skewness. Consistent with these theoretical studies, our measures reflect an investor's preference of asymmetry, and lottery-type assets or strategies in particular. Moreover, they also reflect the degree of short sale constraints on stocks. The more difficult the short sale, the more likely the distribution of the stock return lean towards the upper tail. Thus the expected return will be lower due to likely over-pricing (see, e.g., Acharya, DeMarzo, and Kremer, 2011; Jones and Lamont, 2002). This pattern of behavior is also related to the strategic timing of information by firm managers (see Acharya et al., 2011).

To understand further the difference between skewness and our proposed asymmetry measures, we examine their relation with volatility. Interestingly, we find that skewness, the third moment, is closely related to volatility, the centered second moment, for its impact on expected returns. When the market volatility index is used, skewness negatively affects returns only in high volatility periods. When the idiosyncratic volatility (IVOL) is used, skewness negatively affects returns only for high IVOL stocks. In contrast, the asymmetry measures always have the same direction of effects regardless volatility regimes or high/low IVOL stocks.

We also examine the relationship between asymmetry and returns conditional on investor sentiment. Since its introduction by Baker and Wurgler (2006), the investor sentiment index has been widely used. For example, Stambaugh, Yu, and Yuan (2012) find that asset pricing anomalies are associated with sentiment. Following their analysis, we run regressions of stock returns on skewness conditional on high sentiment periods (when the sentiment is above the 0.5 or 1 standard deviation of the sentiment time series). We find that skewness is negatively and significantly related to the stock returns, but positively and significantly related to the stock returns in the low sentiment periods. This is consistent with the earlier inconclusive impact of skewness on expected returns. In contrast, using our measures of asymmetry, we find that the expected stock returns are negatively related to the stock returns either in high or low sentiment periods.

We further study the relationship between asymmetry and return conditional on market liquidity and the capital gains overhang (CGO). Using the aggregate stock market liquidity (ALIQ) of Pastor, Stambaugh, and Taylor (2014), we find that the relation between skewness and expected return depends on ALIQ. Among stocks only in the high ALIQ regimes, skewness is positively and significantly related to stock returns. In comparison, there is a consistent negative relationship with our measures. Using the CGO measure of An, Wang, Wang, and Yu (2015), we find similar inconsistent results of skewness as in their study, but consistent results of our asymmetry measures. Overall, our asymmetry measures are robust to controls of various market conditions.

The paper is organized as follows. Section 2 presents our new asymmetry measures. Section 3 applies the measures as symmetry tests to simulated data and size portfolios. Section 4 provides the major empirical results. Section 5 examines the relation with volatility, while Section 6 compares the measures further conditional on sentiment, market liquidity and CGO. Section 7 concludes.

2. Asymmetry Measures

In this section, first we introduce our two asymmetry measures and discuss their properties. Then we provide the econometric procedures for their estimation in practice.

Let x be the daily excess return of a stock. If the total asymmetry of the stock is of interest, the raw return may be used. If idiosyncratic asymmetry is of interest, the residual after-adjusting benchmark risk factors may be used. Without loss of generality, we assume that x is standardized with a mean of 0 and a variance of 1. To assess the upside asymmetry of a stock return distribution, we consider its excess tail probability (ETP), which is defined as:

$$E_{\varphi} = \int_{1}^{+\infty} f(x)\, dx - \int_{-\infty}^{-1} f(x)\, dx = \int_{1}^{\infty} [f(x) - f(-x)]\, dx, \tag{1}$$

where the probabilities are evaluated at 1 standard deviation away from the mean.[2] The first term measures the cumulative chance of gains, while the second measures the cumulative chance of losses. If E_{φ} is positive, it implies that the probability of a large loss is less than the probability of a large gain. For an arbitrary concave utility, a linear function of wealth will be its first-order approximation. In this case, if two assets pay the same within one standard deviation of the return, the investor will prefer to hold the asset with greater E_{φ}. In general, investors may prefer stocks with a high upside potential and dislike stocks with a high possibility of big loss (Kelly and Jiang, 2014; Barberis and Huang, 2008; Kumar, 2009; Bali et al., 2011; Han and Hirshleifer, 2015). This implies that, if everything else is equal, the asset expected return will be lower.

Our second measure of distributional asymmetry is an entropy-based measure. Following Racine and Maasoumi (2007) and Maasoumi and Racine (2008), consider a stationary series $\{X_t\}_{t=1}^{T}$ with mean $\mu_x = E[X_t]$ and density function $f(x)$. Let $\tilde{X}_t = -X_t + 2\mu_x$ be a rotation of X_t about its mean, and let $f(\tilde{x})$ be its density function. We say $\{X_t\}_{t=1}^{T}$ is symmetric about the mean if

$$f(x) \equiv f(\tilde{x}) \tag{2}$$

is true almost surely for all x. Any difference between $f(x)$ and $f(\tilde{x})$ is then clearly a measure of asymmetry. Shannon (1948) first introduces entropy measure and Kullback and

[2]Since a certain sample size is needed for a density estimation, we focus on using 1 standard deviation only. The results are qualitatively similar with a 1.5 standard deviation and minor perturbations.

Leibler (1951) make an extension to the concept of relative entropy. However, Shannon's entropy measure is not a proper measure of distance. Maasoumi and Racine (2008) suggest the use of a normalized version of the Bhattacharya-Matusita-Hellinger measure:

$$S_\rho = \frac{1}{2}\int_{-\infty}^{\infty}(f_1^{\frac{1}{2}} - f_2^{\frac{1}{2}})^2 dx, \tag{3}$$

where $f_1 = f(x)$ and $f_2 = f(\tilde{x})$. This entropy measure has four desirable statistical properties: 1) It can be applied to both discrete and continuous variables; 2) If $f_1 = f_2$, that is, the original and rotated distributions are equal, then $S_\rho = 0$. Because of the normalization, the measure lies between 0 and 1; 3) It is a metric, implying that a larger number S_ρ indicates a greater distance and the measure is comparable; and 4) It is invariant under continuous and strictly increasing transformation of the underlying variables.

Assume that the density is smooth enough. We have then the following interesting relationship (see Appendix A.1 for the proof) between S_ρ and moments up to the fourth-order including skewness and kurtosis:

$$S_\rho = c_1 \cdot \sigma^2 + c_2 \cdot \gamma_1\sigma^3 + c_3 \cdot (\gamma_2 + 3)\sigma^4 + o(\sigma^4), \tag{4}$$

where μ is the mean of x, σ^2 is the variance, γ_1 is the skewness, γ_2 is the kurtosis, c_is are constants, and $o(\sigma^4)$ denotes the higher than fourth-order terms. It is clear that S_ρ is related to the skewness. Everything else being equal, higher skewness means a greater S_ρ and greater asymmetry.[3] In practice for stocks, however, it is impossible to control for all other moments. Hence, a high skewness will not necessarily imply a high S_ρ.

Since S_ρ is a distance measure, it does not distinguish between the downside asymmetry

[3] Our measure is also consistent with the intuition in Kumar (2009). He indicates that cheap and volatile stocks with a high skewness attract investors who also tend to invest in state lotteries. However, our measure is more adequate and simple than the one posited by Kumar (2009).

and the upside asymmetry. Hence, for our finance applications, we modify S_ρ by defining our second measure of asymmetry as:

$$S_\varphi = \mathrm{sign}(E_\varphi) \times \frac{1}{2}\left[\int_{-\infty}^{-1}(f_1^{\frac{1}{2}} - f_2^{\frac{1}{2}})^2 dx + \int_{1}^{\infty}(f_1^{\frac{1}{2}} - f_2^{\frac{1}{2}})^2 dx\right]. \tag{5}$$

The sign of E_φ ensures that S_φ has the same sign as E_φ, so that the magnitude of S_φ indicates an upside potential. In fact, S_φ is closely related to E_φ mathematically. While E_φ provides an equal-weighting on asymmetry, S_φ weights the asymmetry by probability mass. Theoretically, S_φ may be preferred as it uses more relevant information from the distribution. However, empirically, their performances can vary from one application to another.

The econometric estimation of E_φ is trivial as one can simply replace the probabilities by the empirical averages. However, the estimation of S_φ requires a substantial amount of computation. In this paper, following Maasoumi and Racine (2008), we use "Parzen-Rosenblatt" kernel density estimator:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{X_i - x}{h}\right), \tag{6}$$

where n is the sample size of the time series data $\{X_i\}$, $k(\cdot)$ is a nonnegative bounded kernel function such as the normal density, and h is a smoothing parameter or bandwidth to be determined below.

In selecting the optimal bandwidth for (6), we use the well-known Kullback-Leibler likelihood cross-validation method (see Li and Racine, 2007 for details). This procedure minimizes the Kullback-Leibler divergence between the actual density and the estimated one:

$$\max_h \mathcal{L} = \sum_{i=1}^{n} \ln\left[\hat{f}_{-i}(X_i)\right], \tag{7}$$

where $\hat{f}_{-i}(X_i)$ is the leave-one-out kernel estimator of $f(X_i)$, which is defined from:

$$\hat{f}_{-i}(X_i) = \frac{1}{(n-1)h} \sum_{j=1 j \neq i}^{n} k\left(\frac{X_i - X_j}{h}\right). \tag{8}$$

Under a weak, time-dependent assumption, which is a reasonable assumption for stock returns, the estimated density converges to the actual density (see, e.g., Li and Racine, 2007). With the above, we can estimate $\hat{S}_\varphi$ by computing the associated integrals numerically.

3. Symmetry Tests

In this section, in order to gain insights on differences between skewness and our new measures, we use these measures as test statistics of symmetry for both simulated data and size portfolios. We show that distribution-based asymmetry measures can capture the asymmetry information that cannot be detected by skewness.

Many commonly used skewness tests, such as that developed by D'Agostino (1970), assume normality under the null hypothesis. Therefore, they are mainly tests of normality that could reject the null when the data is symmetric but not normally distributed. Since we are interested in testing for return symmetry rather than normality, it is inappropriate to apply those tests in our setting. Hence, the skewness test we employ is based on the bootstrap resampling method without assuming normality. As discussed by Horowitz (2001), the bootstrap method with pivotal test statistics can achieve asymptotic refinement over asymptotic distributions. Because of this, we develop the skewness test using pivotized (studentized) skewness as the test statistic. Monte Carlo simulations show that this test has good finite sample sample properties.

The entropy tests of symmetry are carried out in a way similar to Racine and Maasoumi (2007) and Maasoumi and Racine (2008). However, we use the studentized S_ρ as the test statistic that has slightly better finite sample properties in simulations. Overall, the entropy test and the skewness test share the same simulation setup with the only difference being how the test statistics are computed. Due to the heavy computational demands, following Racine and Maasoumi (2007) and Maasoumi and Racine (2008), we determine the significance levels of the tests via a stationary block bootstrap with 399 replications, which seems adequate as perturbations around 399 make almost zero differences in the results.

Consider first the case in which skewness is a good measure. We simulate the data, with sample size of $n = 500$, independently from two distributions: $N(120, 240)$ and $\chi^2(10)$. The first is a normal distribution (symmetric) with a mean of 120 and a variance of 240, and the second is a chi-squared distribution (asymmetric) with 10 degrees of freedom. With $M = 1000$ data sets or simulations (a typical simulation size in this context), the second and third columns of Table 1 report the average statistics of skewness and our new measures. We find that there are no rejections for the normal data and that there are always rejections for the chi-squared distribution. Hence, all the measures work well in this simple case.

[Insert Table 1 about here]

Now consider a more complex situation. The distribution of the data is now defined as the difference of a two beta random variables: Beta(1,3.7)-Beta(1.3,2.3). As plotted in Figure 1, this distribution has a longer left tail and shows negative asymmetry.[4] With the same $n = 500$ sample size and $M = 1000$ simulations as before, the skewness test is now unable to detect any asymmetry. Indeed, the fourth column of Table 1 shows that it has a value of 0.0004 with a t-statistic of 0.13. In contrast, both S_φ and E_φ have

[4]It is a well-defined distribution whose density function is provided by Pham-Gia, Turkkan, and Eng (1993) and Gupta and Nadarajah (2004).

highly significant negative values, which correctly capture the asymmetric feature of the distribution and strongly reject symmetry as expected.

[Insert Figure 1 about here]

To further understand the testing results, Figure 2 plots the two beta distributions: Beta(1,3.70) and Beta(2,12.42). Since both have roughly the same skewness, their difference has a skewness value of 0. This is why the skewness test is totally uninformative about the difference asymmetry. On the other hand, it is clear from Figure 2 that Beta(1,3.70) has a longer right tail and a higher upside asymmetry. This can by captured by both S_φ and E_φ.

[Insert Figure 2 about here]

Finally, we examine the performance of the distribution-based asymmetry measure S_ρ and skewness when they are used in real data. For brevity, consider testing symmetry in only commonly-used size portfolios. The test portfolios we use are the value-weighted and equal-weighted monthly returns of decile stock portfolios sorted by market capitalization. The sample period is from January 1962 to December 2013 (624 observations in total).

Table 2 reports the results for $SKEW$ and S_ρ tests (the results of using E_φ are similar and are omitted). For the value-weighted size portfolios, the entropy test rejects symmetry for the first three smallest and the fifth smallest size portfolios at the conventional 5% level. In contrast, the skewness test can only detect asymmetry for the smallest size portfolio. For the equal-weighted size portfolios, the 1st, 2nd, 7th, and 10th are asymmetric based on the entropy test at the same significance level. In contrast, according to the skewness test, only the 1st and the 7th have significant asymmetry.

[Insert Table 2 about here]

In summary, we find that while skewness can detect asymmetry in certain situations, it may fail completely in others. In contrast, the entropy-based tests can detect asymmetry more effectively than skewness both using real data and in simulations.

4. Empirical Results

4.1. Data

We use return data from the Center for Research in Securities Prices (CRSP) covering from January 1962 to December 2013. The data include all common stocks listed on NYSE, AMEX, and NASDAQ. As usual, we restrict the sample to the stocks with beginning-of-month prices between $1 and $1,500. In order to mitigate the concern of double-counted stock trading volume in NASDAQ, we follow Gao and Ritter (2010) and adjust the trading volume to calculate the turnover ratio ($TURN$) and Amihud (2002) ratio ($ILLIQ$). The latter is normalized to account for inflation and is truncated at 30 in order to eliminate the effect of outliers (Acharya and Pedersen, 2005). Firm size ($SIZE$), book-to-market ratio (BM), and momentum (MOM) are computed in the standard way. Market beta (β) is estimated by using the time-series regression of individual daily stock excess returns on market excess returns, and is updated annually. We use the last month excess returns and risk-adjusted returns (the excess returns that are adjusted for Fama-French three factors, see Brennan, Chordia, and Subrahmanyam, 1998) as proxies for short-term reversals (REV for excess returns and $REVA$ for risk-adjusted returns).

Following Bali et al. (2011), we compute the volatility (VOL) and maximum (MAX) of stock returns as the standard deviation and the maximum of daily returns of the previous month. In addition, we compute the idiosyncratic volatility ($IVOL$) of a stock as the standard deviation of daily idiosyncratic returns of the month. We calculate skewness

($SKEW$), idiosyncratic skewness ($ISKEW$), our proposed asymmetry measures (E_φ and S_φ), and their idiosyncratic counterparts (IE_φ and IS_φ) using the raw return and benchmark adjusted residuals. In order to have accurate estimations, we use daily information for up to 12 months.

There are four additional control variables. We apply two sentiment proxies by Baker and Wurgler (2006, 2007) and Huang, Jiang, Tu, and Zhou (2015). We use BW to denote the sentiment time series index by Baker and Wurgler (2006, 2007), while $HJTZ$ represents the sentiment index proposed by Huang et al. (2015). Since the data provided by Jeffrey Wurgler's website is only available until December 2010, we extend the data to December 2013 (from Guofu Zhou's website). In addition, $HJTZ$ is also obtained from Guofu Zhou's website.[5] VIXM is monthly variance of daily value-weighted market return. Levels of aggregate liquidity ($ALIQ$) is provided by Pastor and Stambaugh (2003) (from Ľuboš Pástor's website).[6] Following Grinblatt and Han (2005), we calculate the capital gain overhang (CGO) for representative investors for each month using a weekly price and turnover ratio. The reference price is the weighted average of past prices in which an investor purchase stocks but never sells. As in Grinblatt and Han (2005), we use information for the past 260 weeks (with at least 200 valid price and turnover observations) for each reference price, which reflects the unimportance of price information older than 5 years. The CGO at week t is the difference between the price at week $t-1$ and the reference price at week t (divided by the price at week $t-1$). In this way, the complicated microstructure effect is avoided.

The details of all above variables are provided in Appendix A.2. Of the variables, it is of interest to examine the correlation of skewness, volatility, and our asymmetry measures.

[5] BW is available at http://people.stern.nyu.edu/jwurgler/; the extended BW and $HJTZ$ are available at http://apps.olin.wustl.edu/faculty/zhou/.

[6] $ALIQ$ is available at http://faculty.chicagobooth.edu/lubos.pastor/.

Table 3 provides the results. For comparison, the table reports results for both the total measures (based on the raw returns) and the idiosyncratic measures. It is observed that the correlations have similar magnitudes in both cases. $ISKEW$ has very small correlations with IE_{φ} or IS_{φ}. This highlights the need of using our proposed asymmetry measures rather than skewness as a proxy to capture asymmetry. As expected, IE_{φ} or IS_{φ} have a high correlation of over 67% as both measure distribution asymmetry. The volatility has approximately 8% correlation with the skewness and a much lower correlation with IE_{φ} or IS_{φ}. The correlation analysis shows that the new asymmetry measure captures information beyond volatility and skewness.

[Insert Table 3 about here]

4.2. Firm Characteristics and Asymmetries

In this subsection, we examine the types of stock that are associated with asymmetries as measured by $ISKEW$, IE_{φ} and IS_{φ}. Using idiosyncratic asymmetry measures as dependent variables, we run Fama-Macbeth regressions on common characteristics: $SIZE$, BM, MOM, $TURN$, $ILLIQ$, and the market beta (β):

$$IA_{i,t} = a_t + B_t X_{i,t} + \epsilon_{i,t}, \tag{9}$$

where $IA_{i,t}$ is one of the three asymmetry measures of the firm i and $X_{i,t}$ are firm characteristics. Idiosyncratic asymmetry measures are winsorized at a 0.5 percentile and 99.5 percentile. The Fama-MacBeth standard errors are adjusted using the Newey and West (1987) correction with three lags.[7]

Table 4 provides the results. Consistent with other studies such as Boyer et al. (2010)

[7] All results are qualitatively similar if we use up to 24 lags.

and Bali et al. (2011), $ISKEW$ is negatively related to $SIZE$ and BM and positively related to MOM, $ILLIQ$, and market beta (β), while is insignificantly related to $TURN$. Interestingly, despite low correlations, IE_φ and IS_φ are significantly related to all the characteristics except $TURN$ in the same direction as skewness. A likely reason is that all of these characteristics are related to the asymmetry of firms. As a result, different measures show similar relationships to these characteristics.

In contrast to skewness, IE_φ and IS_φ are positively and significantly related to $TURN$. This result is consist with Kumar (2009), who finds that lottery-type stocks have much higher turnover ratios. Since our proposed asymmetry measures can capture the property of asymmetric distribution of lottery-type stocks, it is not surprising that they are positively and significantly related to turnover ratios.

[Insert Table 4 about here]

4.3. Expected Returns and Asymmetries

In this subsection, we examine the power of our new asymmetry measures in explaining the cross-section of stock returns and then compare them with skewness, the previously commonly-used proxy for asymmetry.

One of the fundamental problems in finance is to understand what factor loadings or characteristics can explain the cross-section of stock returns. To compare the power of our new asymmetry measures and skewness, we run the following standard Fama-MacBeth regressions:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} IA_{\varphi,i,t} + \lambda_{2,t} ISKEW_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1}, \tag{10}$$

where $R_{i,t+1}$ is the excess return, the difference between the monthly stock return and one-month T-bill rate on stock i at time t, $IA_{\varphi,i,t}$ is either $IS_{\varphi,i,t}$ or $IE_{\varphi,i,t}$ at t, and $X_{i,t}$ is a set of control variables including $SIZE$, BM, MOM, $TURN$, $ILLIQ$, β, MAX, REV, VOL, or $IVOL$ for the full specification.

Table 5 reports the results. When using either $IE_{\varphi,i,t}$ or $IS_{\varphi,i,t}$ alone, their regression slopes are -3.4598 and -0.8584 (the third and fourth columns), respectively. Both of the slopes are significant at the 1% level and their signs are consistent with the theoretical prediction that the right-tail asymmetry is negatively related to expected returns. In contrast, the slope on $ISKEW$ is slightly positive, 0.0113 (see the second column on the univariate regression), and is statistically insignificant. Hence, it is inconclusive as to whether skewness can explain the cross-section of stock returns over the period covering January 1962 to December 2013.[8]

[Insert Table 5 about here]

The explanatory power of $IE_{\varphi,i,t}$ or $IS_{\varphi,i,t}$ is robust to various controls. Adding $ISKEW$ into the univariate regression of $IE_{\varphi,i,t}$ (the fifth column), the slope changes slightly, from -3.4598 to -3.7902, and remains statistically significant at 1%. With additional controls, especially the market beta (β) and the MAX variable of Bali et al. (2011), columns 6–8 of the table show that neither the sign nor the significance level have altered for $IE_{\varphi,i,t}$. Similar conclusions hold true for $IS_{\varphi,i,t}$.

Since the value-weighted excess market return, size (SMB), and book-to-market (HML) factors are major statistical benchmarks for stock returns, we consider whether our results are robust using risk-adjusted returns. We remove the systematic components from the returns by subtracting the products of their beta times the market, size, and book-to-market factors (see Brennan et al., 1998). Denote the risk-adjusted return of stock i by

[8] Instead of using the realized skewness $ISKEW$, one can use the estimated future skewness as defined by Boyer et al. (2010) or Bali et al. (2011). These results are available upon request and remain insignificant.

RA_i. We then re-run the earlier regressions using the adjusted returns as the dependent variable:

$$RA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} IA_{\varphi,i,t} + \lambda_{2,t} ISKEW_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1}, \tag{11}$$

where $X_{i,t}$ is a set of control variables excluding the market beta.

Table 6 reports the results. In this alternative model specification, skewness is still insignificant, although now the value is slightly negative. In contrast, both the effects of $IE_{\varphi,i,t}$ and $IS_{\varphi,i,t}$ are negatively significant as seen before. The results reaffirm that our new asymmetry measures have significant power in explaining the cross-section of stock returns, while the skewness measure barely matters.[9]

[Insert Table 6 about here]

4.4. Asymmetry Portfolios

In this subsection, we examine the performances of portfolios sorted by skewness, $IE_{\varphi,i,t}$, and $IS_{\varphi,i,t}$, respectively. This provides an alternative evaluation with respect to the previous Fama-MacBeth regressions in terms of assessing the ability of these asymmetry measures in explaining the cross-section of stock returns.

Table 7 reports the results on the skewness decile portfolios. These results are equal weighted as usual, from the lowest skewness level to the highest, as well as the return spread of the highest minus the lowest portfolios. The second column of the table clearly displays no monotonic pattern. The return difference is 0.073% per month, which is neither economically nor statistically significant. Hence, stocks with high skewness do not necessarily imply a low return. Theoretically, this is quite understandable. Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2008), and Han and Hir-

[9] If we further remove the tail risk factor proposed by Kelly and Jiang (2014), the results are still qualitatively similar.

shleifer (2015) generally imply that high asymmetry leads to a lower return or a greater upside asymmetry is associated with a lower expected return. Since high skewness does not always lead to high asymmetry, its theoretical impact remains generally unclear.

From an asset pricing perspective, it is of interest to examine whether the portfolio alphas are significant. The third and fourth columns of Table 7 report the results based on the CAPM and Fama and French (1993) 3-factor alphas. While some deciles appear to have some alpha values, the spread portfolio has a CAPM alpha of 0.077% per month and a Fama-French alpha of 0.048% per month, both of which are small and insignificant. The results show overall that skewness risk does not appear to earn abnormal returns relative to the standard factor models.

[Insert Table 7 about here]

Consider now asymmetry measure $IE_{\varphi,i,t}$. The second column of Table 8 shows clearly an approximate pattern of decreasing returns across the deciles. Moreover, the spread portfolio has a (negatively) large value of -0.179% per month, which is statistically significant at the 1% level. The annualized return is 2.15%, which is economically significant. In addition, its alphas are large and significant. Overall, there is strong evidence that a high $IE_{\varphi,i,t}$ leads to a low return, which is consistent with the theory.

Finally, Table 9 provides the results on the decile portfolios sorted by $IS_{\varphi,i,t}$. The decreasing pattern of returns across the decile is similar to the case of $IE_{\varphi,i,t}$ and the spread earns significant alphas.[10] This result is not surprising as both measures are similar and their time-series average of cross-sectional correlation is around 68%.

[Insert Table 8 about here]

[10]The results are similar when applying Fama and French (2015) 5-factor models.

[Insert Table 9 about here]

In summary, the empirical results support that while inconclusive with skewness, both $IE_{\varphi,i,t}$ and $IS_{\varphi,i,t}$ are useful measures of asymmetry. Thus, they can explain well the asymmetry of the cross-section of stock returns in a way consistent with theory.

5. Relation to Volatility

In this section, we examine how skewness and asymmetry measures perform by controlling volatility effects in two ways. The first is to define volatility regimes based on market volatility index (VIX). The second is to use idiosyncratic volatility (IVOL) to define high and low IVOL stocks for running regressions or to use the value of IVOLs for sorting stocks.

5.1. VIX

Based on VIX, high volatility regime is defined as those months when the realized VIX-market volatility (VIXM) is above its mean, while the low VIX volatility regime is defined as those months when realized VIXM is below its mean.

Consider first the regressions of the excess returns on $ISKEW$ and various controls:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} ISKEW_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1}, \tag{12}$$

where $X_{i,t}$ is a vector of control variables as before. The only difference now is that we run the regressions in high and low VIX regimes separately.

Table 10 reports the results. Columns 2–5 show that, skewness always has a significant and negative effect on expected return when VIX is high, whether or not there are other various controls in place. However, when the VIX is low, their loadings, (Columns 6–9), are always positive. The opposite sign of the slopes during high VIX or low VIX periods is consistent with the findings of Bali et al. (2011), that there is no apparent relationship between the skewness and the cross-sectional average returns.

[Insert Table 10 about here]

In comparison, we run the same Fama-MacBeth regressions of the excess returns on IE_φ and IS_φ conditional on high and low VIX periods, respectively. Table 11–12 show that both IE_φ and IS_φ always have negative loadings in both of the VIX regimes, although the magnitudes and statistical significance varied.

[Insert Table 11 about here]

[Insert Table 12 about here]

In short, while skewness explains asset returns differently under different VIX regimes, IE_φ and IS_φ provide consistent results regardless of high or low VIX regimes.

5.2. Idiosyncratic Volatility

We examine the role of IVOL in two ways. To conduct the first approach, we define high $IVOL$ stocks as those for which the realized $IVOL$ is above its monthly cross-sectional mean, while low $IVOL$ stocks are those for which the realized $IVOL$ is below its monthly cross-sectional mean. Then, we first perform the similar regressions (equation 12) of the excess returns on $ISKEW$ and various controls, but within high $IVOL$ stocks and low $IVOL$ stocks, respectively. Table 13 presents the results. Columns 2–4 show that skewness has a negative effect on expected return within high $IVOL$ stocks. However, within low $IVOL$ stocks, its loading (Column 6) varies with various other controls.

[Insert Table 13 about here]

Unlike skewness, Tables 14-15 show that both IE_φ and IS_φ almost always have negative loadings within the $IVOL$s of stocks. The only exception is the case of the univariate regression on IS_φ within low $IVOL$ stocks. However, the magnitude and statistical significance level is close to 0 in that specific case.

[Insert Table 14 about here]

[Insert Table 15 about here]

In the second approach, we conduct a double-sort analysis to check the $IVOL$ effect on asymmetry. At the beginning of each month from 1962 to 2013, we first sort stocks by IVOL into quintile portfolios. Then, within each $IVOL$ portfolio, we sort stocks further into quintile portfolios by one of the following asymmetry measures: $ISKEW$, IE_φ, or IS_φ.

Table 16 reports the equal-valued excess returns of some of the selected portfolios. The negative spread excess return of $P5 - P1$ (the difference between the highest and lowest skewness stocks) only appears in the highest quintile of $IVOL$, which is -0.140%. Among the other four $IVOL$ quintile portfolios, three $ISKEW$ spread portfolios have significant positive returns, confirming that skewness is sensitive to the $IVOL$ level. In contrast, the spread portfolios for IE_φ and IS_φ have mostly significant and negative returns across the $IVOL$ quintiles.

[Insert Table 16 about here]

In short, both Fama-MacBeth regressions and double-sort analysis show that IE_φ and IS_φ are much less sensitive to $IVOL$ when compared with skewness.

6. Further Comparison

In this section, we first examine how skewness and asymmetry measures perform under different market regimes determined by investor sentiment and aggregate stock market liquidity, respectively. Then, study their interaction with the capital gains overhang.

6.1. Sentiment

In this subsection, we examine how asymmetry measures vary during high and low sentiment periods. Stambaugh et al. (2012) and Stambaugh, Yu, and Yuan (2015) find that anomalous returns are high following high sentiment periods because mispricing is likely to be more prevalent when investor sentiment is high. Since asymmetry measures are related to lottery type stocks, it is of interest to investigate whether their effects on expected return are related to sentiment.

Following Stambaugh et al. (2012, 2015), we run Fama-MacBeth regressions in two regimes. The first is high sentiment periods, which are defined here as those months when the Baker and Wurgler (2006) sentiment index (BW index henceforth) is one standard deviation above its mean. The second regime is low sentiment periods when the BW index is one standard deviation below its mean.[11] Then we run the same regressions (equation 12) of the excess returns on $ISKEW$ and various controls as before except that now the regressions are carried out in high and low sentiment periods separately.

Table 17 reports the results. Columns 2–5 show that, conditional on high sentiment, skewness always has a significant negative effect on expected return whether or not there are other various controls in place. However, when the sentiment is low, their loadings (Columns 6–9), are always positive and significant. The sign change of the slopes sheds light on the earlier mixed evidence on the ability of skewness to explain the returns consistently.

[11] The results are similar with the PLS sentiment index of Huang et al. (2015).

[Insert Table 17 about here]

Consider now the Fama-MacBeth regressions of the excess returns on IE_φ conditional on high and low sentiment periods. Table 18 shows that IE_φ always has negative loadings, regardless of the sentiment regimes. However, the statistical significance is much stronger in high sentiment periods than in low ones. The same pattern is observed on IS_φ in Table 19.

[Insert Table 18 about here]

[Insert Table 19 about here]

Note the the above results are for raw returns. If the risk adjusted returns are used, the results are qualitatively similar (not reported here). Overall, the results show that skewness is quite sensitive to sentiment, while IE_φ and IS_φ are much less so.

6.2. Aggregate Stock Market Liquidity

Pastor et al. (2014) point out that Aggregate Stock Market Liquidity ($ALIQ$) is the proxy for potential mispricing besides sentiment, and this mispricing is likely to be more prevalent when illiquidity is high. In this subsection, we further examine how asymmetry measures vary during high and low $ALIQ$ periods using Fama-MacBeth regressions. High $ALIQ$ periods are defined as those months when levels of aggregate liquidity ($ALIQ$) provided by Pastor and Stambaugh (2003) is above its mean. Likewise, low $ALIQ$ periods are defined as those months when aggregate liquidity is below its mean.

We conduct the similar regressions (equation 12) of the excess returns on $ISKEW$ and various controls for high $ALIQ$ and low $ALIQ$ periods separately. Results are shown in Table 20. The univariate regression results show a positive relation between the $ISKEW$

and the cross-section of future stock returns during high $ALIQ$ periods, while the relation changed to negative for low $ALIQ$ periods. The sign of the slopes may change when adding other controls.

[Insert Table 20 about here]

The Fama-MacBeth regression results of the excess returns on IE_{φ} conditional on high and low $ISKEW$ periods are presented in Table 21. IE_{φ} is always negative and statistically significantly related to expected returns for the two $ALIQ$ regimes. The same pattern is observed on IS_{φ} in Table 22, although the negative loading is statistically insignificant for the univariate regression during the high $ALIQ$ periods.

[Insert Table 21 about here]

[Insert Table 22 about here]

Together with previous subsection' observations, the negative relationship between skewness and expected return only exists during high sentiment periods or high aggregate market illiquidity periods. Our new asymmetry measures are not subject to these problems and are consistent with theoretical models such as Barberis and Huang (2008) and Han and Hirshleifer (2015), which predict that high upside asymmetry means lower expected return.

6.3. Capital Gains Overhang

In this subsection, we examine how the effect of asymmetry on stock returns vary with the capital gains overhang (CGO) using different measures. Recently, An et al. (2015) find that the existence of skewness preference depends on the CGO level. It is of interest to investigate whether our new asymmetry measures also behave in a similar way as skewness, which only captures partial asymmetry of the data.

Following Grinblatt and Han (2005), CGO is the normalized difference between the current stock price and the reference price. The reference price is the weighted average of past stock prices with the weight based on past turnover. A high CGO generally implies large capital gains. An et al. (2015) find that the skewness only matters for stocks with capital loss, but it is still unclear whether the relationship between asymmetry and expected return depends on CGO even if we use a more accurate measure of asymmetry.

Let DUM_CGO be the CGO dummy variable which equals one if the stock experiences a capital gain ($CGO \geq 0$) and equals zero otherwise. To assess its interaction with $ISKEW$, we modify the earlier Fama-MacBeth regressions of the excess returns on $ISKEW$ to:

$$\begin{aligned} R_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}DUM\_CGO_{i,t} + \lambda_{3,t}ISKEW_{i,t} \\ &+\lambda_{4,t}DUM\_CGO_{i,t} \times ISKEW_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1}, \end{aligned} \tag{13}$$

where $X_{i,t}$ is a vector of other firm characteristics.

Table 23 reports the results. Without any controls for other firm characteristics, the third column of the table shows that the effect of skewness on stock return changes with the CGO dummy. The rest of the columns provide similar results that are consistent with finding of An et al. (2015) indicating the skewness preference depends on the CGO: investors like positively skewed stocks only when they experience a capital loss. In other words, skewness alone appears to only work for a subset of stocks.

[Insert Table 23 about here]

Consider now either IE_φ or IS_φ. Replacing $ISKEW$ by either of them, we re-run previous regressions. Table 24-25 report the results. It is clear that IE_φ or IS_φ always matter regardless of stocks where average investors are experiencing a capital gain or loss. Moreover, in all cases, there are no strong interactive effects between our new measures and CGO dummy at the 5% level. Hence, using our new asymmetry measures, the preference of positive asymmetric stocks is a general phenomenon that is invariant with respect to DUM_CGO.

[Insert Table 24 about here]

[Insert Table 25 about here]

To further examine the effect of CGO, we conduct a double-sort analysis. At the beginning of each month from 1962 to 2013, we first sort stocks by CGO into quintile portfolios. Then, within each CGO portfolio, we sort stocks into quintile portfolios by one of the following asymmetry measures: $ISKEW$, IE_φ, or IS_φ. For brevity, table 26 reports the equal-valued excess returns of some of the selected portfolios. Only in the lowest quintile of CGO do we see a return on the spread portfolio of $P5-P1$ (the difference between the highest and lowest skewness stocks) of -0.465%, which is significant and thus reaffirms that skewness is tied to the CGO level. In contrast, the spread portfolios for IE_φ and IS_φ have mostly significant returns across the CGO quintiles. Therefore, while the effect of skewness is closely related to CGO, our new measures of asymmetry are fairly robust.

[Insert Table 26 about here]

7. Conclusion

In this paper, we propose two distribution-based measures of stock return asymmetry to substitute skewness in asset pricing tests. These measures are mathematically more accurate than skewness. The first measure is based on the probability difference of upside potential and downside loss of a stock, while the second is based on entropy adapted from the Bhattacharya-Matusita-Hellinger distance measure in Racine and Maasoumi (2007). In contrast to the widely-used skewness measure, our measures make use of the entire tail distribution beyond the third moment. As a result, they capture asymmetry more effectively as shown in our simulations and empirical results.

Based on our new measures, we find that in the cross section of stock returns, greater tail asymmetries imply lower average returns. This is statistically significant not only at the firm-level, but also in the cross-section of portfolios sorted by the new asymmetry measures. In contrast, the empirical results from skewness is inconclusive. Our empirical results are consistent with the predictions of theoretical models as seen in Barberis and Huang (2008) and Han and Hirshleifer (2015).

Appendix

In this appendix, we provide the proof of Equation (4) and detailed definitions of all the variables used in the paper.

A.1 Proof of Equation (4)

Following Maasoumi and Theil (1979), let $Ex = \mu_x = \mu$, $Var(x) = \sigma^2$, skewness $\gamma_1 = \frac{E(x-\mu)^3}{\sigma^3}$, kurtosis $\gamma_2 = \frac{E(x-\mu)^4}{\sigma^4} - 3$, and $g(x) = \frac{f(-x+2\mu)}{f(x)}$. We then have

$$\begin{aligned} S_\rho &= \tfrac{1}{2}E_x\Big[1 - g(x)^{\frac{1}{2}}\Big]^2 \\ &= \tfrac{1}{2}E_x\Big[g(x)\Big] - E_x\Big[g(x)^{\frac{1}{2}}\Big] + \tfrac{1}{2}. \end{aligned} \tag{14}$$

Using the Taylor expansion of $g(x)$ at the mean μ,

$$\begin{aligned} g(x) &= g(\mu) + g^{(1)}(\mu)(x-\mu) + \tfrac{g^{(2)}(\mu)}{2!}(x-\mu)^2 + \tfrac{g^{(3)}(\mu)}{3!}(x-\mu)^3 \\ &+ \tfrac{g^{(4)}(\mu)}{4!}(x-\mu)^4 + o((x-\mu)^4), \end{aligned} \tag{15}$$

we have

$$\begin{aligned} E\big[g(x)\big] &= g(\mu) + \tfrac{g^{(2)}(\mu)}{2!}\sigma^2 + \tfrac{g^{(3)}(\mu)}{3!}\gamma_1\sigma^3 \\ &+ \tfrac{g^{(4)}(\mu)}{4!}(\gamma_2+3)\sigma^4 + o(\sigma^4). \end{aligned} \tag{16}$$

Similarly, by applying the Taylor expansion of $g(x)^{\frac{1}{2}}$ at the mean μ, we obtain

$$\begin{aligned} g(x)^{\frac{1}{2}} &= g(\mu)^{\frac{1}{2}} + (g(x)^{\frac{1}{2}})^{(1)}|_{x=\mu}(x-\mu) + \tfrac{(g(x)^{\frac{1}{2}})^{(2)}|_{x=\mu}}{2!}(x-\mu)^2 + \tfrac{(g(x)^{\frac{1}{2}})^{(3)}|_{x=\mu}}{3!}(x-\mu)^3 \\ &+ \tfrac{(g(x)^{\frac{1}{2}})^{(4)}|_{x=\mu}}{4!}(x-\mu)^4 + o((x-\mu)^4). \end{aligned} \tag{17}$$

Using the expectation, we obtain

$$
\begin{aligned}
E\big[g(x)^{\frac{1}{2}}\big] \quad &= g(\mu)^{\frac{1}{2}} + \tfrac{(g(x)^{\frac{1}{2}})^{(2)}|_{x=\mu}}{2!}\sigma^2 + \tfrac{(g(x)^{\frac{1}{2}})^{(3)}|_{x=\mu}}{3!}\gamma_1\sigma^3 \\
&+ \tfrac{(g(x)^{\frac{1}{2}})^{(4)}|_{x=\mu}}{4!}(\gamma_2+3)\sigma^4 + o(\sigma^4).
\end{aligned} \tag{18}
$$

Hence, (14) becomes

$$
\begin{aligned}
S_\rho \quad &= \tfrac{1}{2} - g(\mu)^{\frac{1}{2}} + \tfrac{1}{2}g(\mu) + \Big[\tfrac{g^{(2)}(\mu)}{4} - \tfrac{(g(x)^{\frac{1}{2}})^{(2)}|_{x=\mu}}{2}\Big]\sigma^2 \\
&+\Big[\tfrac{g^{(3)}(\mu)}{12} - \tfrac{(g(x)^{\frac{1}{2}})^{(3)}|_{x=\mu}}{6}\Big]\gamma_1\sigma^3 \\
&+\Big[\tfrac{g^{(4)}(\mu)}{48} - \tfrac{(g(x)^{\frac{1}{2}})^{(4)}|_{x=\mu}}{24}\Big](\gamma_2+3)\sigma^4 + o(\sigma^4) \\
&= \tfrac{1}{2} - g(\mu)^{\frac{1}{2}} + \tfrac{1}{2}g(\mu) \\
&+\Big[\tfrac{g^{(2)}(\mu)}{4} + \tfrac{1}{8}g(\mu)^{-\frac{3}{2}}(g^{(1)}(\mu))^2 - \tfrac{1}{4}g(\mu)^{-\frac{1}{4}}g^{(2)}(\mu)\Big]\sigma^2 \\
&+\Big[\tfrac{g^{(3)}(\mu)}{12} - \tfrac{1}{16}g(\mu)^{-\frac{5}{2}}(g^{(1)}(\mu))^3 + \tfrac{1}{8}g(\mu)^{-\frac{3}{2}}g^{(1)}(\mu)g^{(2)}(\mu) - \tfrac{1}{12}g(\mu)^{-\frac{1}{2}}g^{(3)}(\mu)\Big]\gamma_1\sigma^3 \\
&+\Big[\tfrac{g^{(4)}(\mu)}{48} + \tfrac{5}{128}g(\mu)^{-\frac{7}{2}}(g^{(1)}(\mu))^4 - \tfrac{3}{32}g(\mu)^{-\frac{5}{2}}(g^{(1)}(\mu))^2g^{(2)}(\mu) + \tfrac{1}{32}g(\mu)^{-\frac{3}{2}}(g^{(2)}(\mu))^2 \\
&+\tfrac{1}{24}g(\mu)^{-\frac{3}{2}}g^{(1)}(\mu)g^{(3)}(\mu) - \tfrac{1}{48}g(\mu)^{-\frac{1}{2}}g^{(4)}(\mu)\Big](\gamma_2+3)\sigma^4 + o(\sigma^4), \\
&= \Big[\tfrac{g^{(2)}(\mu)}{4} + \tfrac{1}{8}(g^{(1)}(\mu))^2 - \tfrac{1}{4}g^{(2)}(\mu)\Big]\sigma^2 \\
&+\Big[\tfrac{g^{(3)}(\mu)}{12} - \tfrac{1}{16}(g^{(1)}(\mu))^3 + \tfrac{1}{8}g^{(1)}(\mu)g^{(2)}(\mu) - \tfrac{1}{12}g^{(3)}(\mu)\Big]\gamma_1\sigma^3 \\
&+\Big[\tfrac{g^{(4)}(\mu)}{48} + \tfrac{5}{128}(g^{(1)}(\mu))^4 - \tfrac{3}{32}(g^{(1)}(\mu))^2g^{(2)}(\mu) + \tfrac{1}{32}(g^{(2)}(\mu))^2 \\
&+\tfrac{1}{24}g^{(1)}(\mu)g^{(3)}(\mu) - \tfrac{1}{48}g^{(4)}(\mu)\Big](\gamma_2+3)\sigma^4 + o(\sigma^4),
\end{aligned} \tag{19}
$$

which is Equation (4) with the constants defined accordingly. Q.E.D.

A.2 Variable Definitions

- E_φ: The excess tail probability or total excess tail probability of stock i (at one standard deviation) in month t is defined as (1), and x is the standardized daily excess return. For stock i in month t, we use daily returns from month $t-1$ to $t-12$ to calculate E_φ.
- S_φ: S_φ or total S_φ of stock i in month t is defined as (5), and x is the standardized daily excess return. For stock i in month t, we use daily returns from month $t-1$ to $t-12$ to calculate S_φ.
- IE_φ: The idiosyncratic E_φ of stock i (at one standard deviation) in month t is defined as (1), and x is the standardized residual after adjusting market effect. Following Bali et al. (2011) and Harvey and Siddique (2000), when estimating idiosyncratic measurements other than volatility, we utilize the daily residuals $\epsilon_{i,d}$ in the following expression:

$$R_{i,d} = \alpha_i + \beta_i \cdot R_{m,d} + \gamma_i \cdot R_{m,d}^2 + \epsilon_{i,d}, \tag{20}$$

  where $R_{i,d}$ is the excess return of stock i on day d, $R_{m,d}$ is the market excess return on day d, and $\epsilon_{i,d}$ is the idiosyncratic return on day d. We use daily residuals $\epsilon_{i,d}$ from month $t-1$ to $t-12$ to calculate IE_φ.
- IS_φ: The idiosyncratic S_φ of stock i (at one standard deviation) in month t is defined as (5) and x is the standardized residual after adjusting market effect. Similar to IE_φ, we use daily residuals $\epsilon_{i,d}$ (20) from month $t-1$ to $t-12$ to calculate IS_φ.
- VOLATILITY (VOL): VOL or total volatility of stock i in month t is defined as the standard deviation of daily returns within month $t-1$:

$$VOL_{i,t} = \sqrt{var(R_{i,d})}, d = 1, ..., D_{t-1}, \tag{21}$$

where D_t is the number of trading days for month t.

- IDIOSYNCRATIC VOLATILITY ($IVOL$): Following Bali et al. (2011), idiosyncratic volatility ($IVOL$) of stock i in month t is defined as the standard deviation of daily idiosyncratic returns within month $t-1$. In order to calculate return residuals, we assume a single-factor return generating process:

$$R_{i,d} = \alpha_i + \beta_i \cdot R_{m,d} + \epsilon_{i,d}, d = 1, ..., D_t, \tag{22}$$

where $\epsilon_{i,d}$ is the idiosyncratic return on day d for stock i, and D_t is the number of trading days for month t. $IVOL$ of stock i in month t is then defined as follows:

$$IVOL_{i,t} = \sqrt{var(\epsilon_{i,d})}, d = 1, ..., D_{t-1}. \tag{23}$$

- SKEWNESS ($SKEW$): skewness or total skewness of stock i in month t is computed using daily returns from month $t-1$ to $t-12$, which is the same as seen in Bali et al. (2011):

$$SKEW_{i,t} = \frac{1}{D_t}\sum_{d=1}^{D_t}(\frac{R_{i,d} - \mu_i}{\sigma_i})^3, \tag{24}$$

where D_t is the number of trading days in a year, $R_{i,d}$ is the excess return on stock i on day d, μ_i is the mean of returns of stock i in a year, and σ_i is the standard deviation of returns of stock i in a year.

- IDIOSYNCRATIC SKEWNESS ($ISKEW$): Idiosyncratic skewness of stock i in month t is computed using the daily residuals $\epsilon_{i,d}$ in (20) instead of the stock excess returns in (24) from month $t-1$ to $t-12$.

- MARKET BETA (β):

$$R_{i,d} = \alpha + \beta_{i,y} \cdot R_{m,d} + \epsilon_{i,d}, d = 1, ..., D_y, \tag{25}$$

where $R_{i,d}$ is the excess return of stock i on day d, $R_{m,d}$ is the market excess return on day d, and D_y is the number of trading days in year y. β is annually updated.

- MAXIMUM (MAX): MAX is the maximum daily return in a month following Bali et al. (2011):

$$MAX_{i,t} = max(R_{i,d}), d = 1, ..., D_{t-1}, \tag{26}$$

where $R_{i,d}$ is the excess return of stock i on day d and D_{t-1} is the number of trading days in month $t-1$.

- SIZE ($SIZE$): Following the existing literature, firm size at each month t is measured using the natural logarithm of the market value of equity at the end of month $t-1$.
- BOOK-TO-MARKET (BM): Following Fama and French (1992, 1993), a firm's book-to-market ratio is calculated using the market value of equity at the end of December of the last year and the book value of common equity plus balance-sheet deferred taxes for the firm's fiscal year ending in the prior calendar year. We assume book value is available six months after the reporting date. Our measure of book-to-market ratio at month t, BM, is defined as the natural log of the book-to-market ratio at the end of month $t-1$.
- MOMENTUM (MOM): Following Jegadeesh and Titman (1993), the momentum effect of each stock in month t is measured by the cumulative return over the previous six months with the previous month skipped; i.e., the cumulative return from month $t-7$ to month $t-2$.
- SHORT-TERM REVERSAL (REV): Following Jegadeesh (1990), Lehmann (1990), and Bali et al. (2011)'s definition, reversal for each stock in month t is defined as the excess return on the stock over the previous month; i.e., the return in month $t-1$.
- ADJUSTED SHORT-TERM REVERSAL ($REVA$): This is defined as the adjusted-return (the excess return that is adjusted for Fama-French three factors, see Brennan

et al., 1998) over the previous month.

- TURNOVER ($TURN$): $TURN$ is calculated monthly as the adjusted monthly trading volume divided by month-end shares outstanding.
- ILLIQUIDITY ($ILLIQ$): Following Amihud (2002), we first calculate the ratio of absolute price change to dollar trading volume for each stock each day. Then we take the average of the ratio for the month if the number of observations is higher than 15 in the month. Following Acharya and Pedersen (2005), we normalize the Amihud ratio and truncate it at 30.
- CAPITAL GAINS OVERHANG (CGO): The capital gains overhang (CGO) at week w is defined as:

$$CGO_w = \frac{P_{w-1} - RP_w}{P_{w-1}}, \tag{27}$$

where P_{w-1} is the stock price at the end of week $w-1$ and RP_w is the reference price for each individual stock, which is defined as follows:

$$RP_w = k^{-1} \sum_{n=1}^{260} (V_{w-n} \prod_{\tau=1}^{n-1} (1 - V_{w-n+\tau})) P_{w-n}, \tag{28}$$

where V_w is the turnover in week w; and k is the constant that makes the weights on past prices sum to one.

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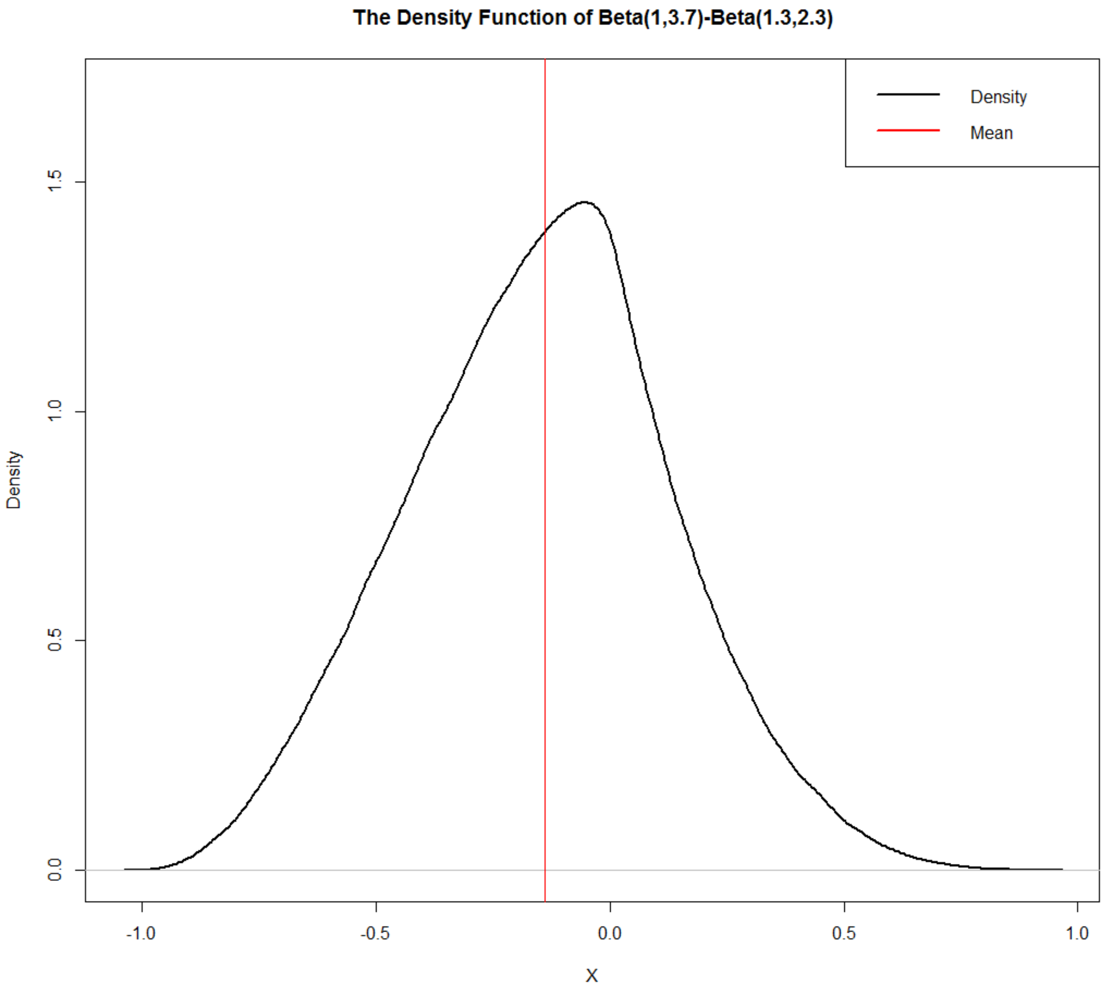

Figure 1: Asymmetric Distribution with skewness=0

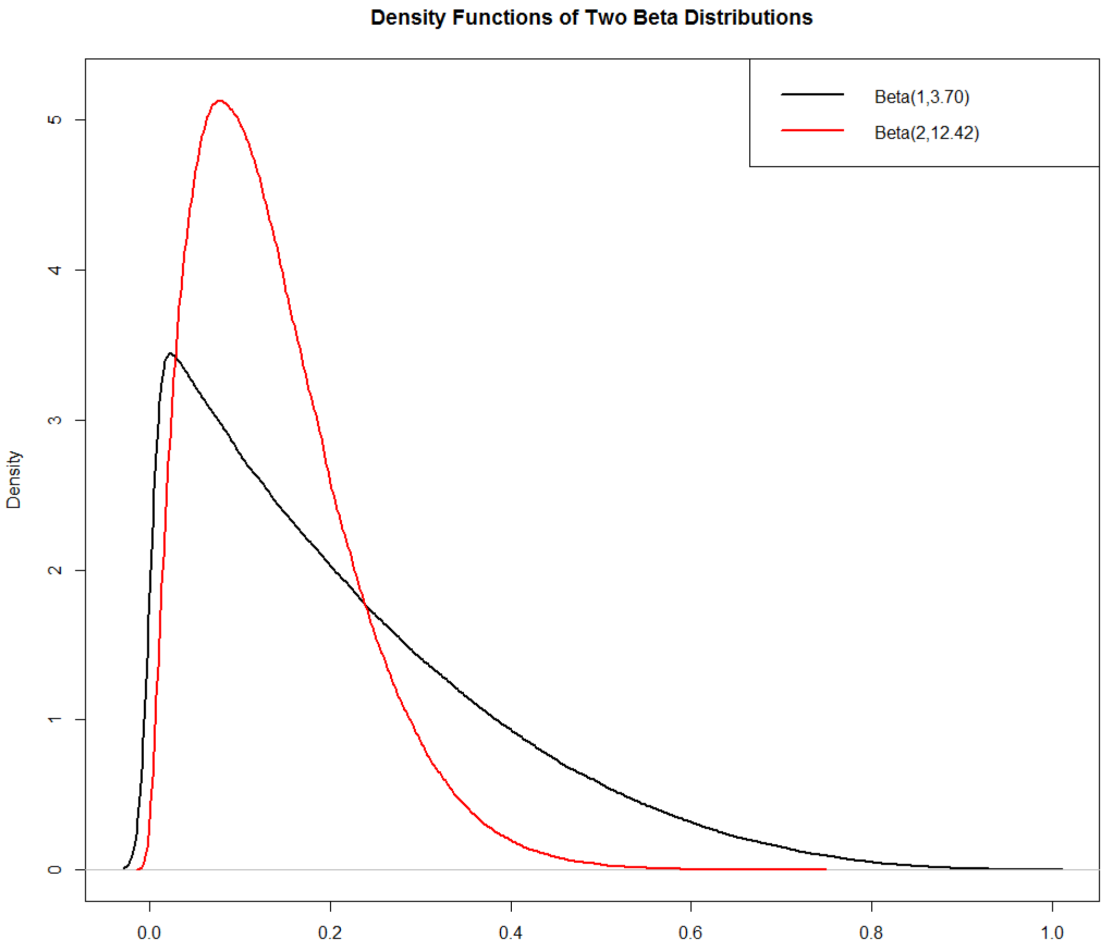

Figure 2: Beta Distributions with skewness=1

Table 1: Simulations

The table provides the average values and associated t-statistics (in parentheses) of skewness($SKEW$), E_φ, and S_φ for 1,000 data sets with sample size of $n = 500$, drawn from a normal distribution, a chi-squared distribution and a Beta difference distribution, respectively. Significance at 1% level is indicated by ***.

	$N(120, 240)$	$\chi^2(10)$	Beta(1,3.7)-Beta(1.3,2.3)
$SKEW$	0.0038	0.8802***	0.0004
	(1.05)	(170.56)	(0.13)
E_φ	0.0002	0.0035***	-0.0127***
	(0.57)	(12.33)	(-45.10)
S_φ	0.0004	0.0554***	-0.0304***
	(0.44)	(11.95)	(-33.60)

Table 2: Asymmetry of Size Portfolios

The table reports the skewness and entropy tests of symmetry for both value- and equal-weighted size decile portfolios. The P-values are computed based on bootstrap and the data are monthly from January 1962 to December 2013.

	Value Weighted Size				Equal Weighted Size			
Portfolios	$SKEW$	P-value	$S_\rho \times 100$	P-value	$SKEW$	P-value	$S_\rho \times 100$	P-value
1(lowest)	0.936	0.023	1.323	0.015	1.278	0.020	2.294	0.000
2	0.822	0.168	1.217	0.013	1.100	0.185	1.157	0.035
3	0.424	0.118	0.788	0.038	0.943	0.140	0.727	0.068
4	0.174	0.634	0.183	0.622	0.720	0.308	0.399	0.253
5	0.001	1.000	0.385	0.010	1.094	0.251	0.415	0.100
6	0.079	0.597	0.293	0.206	0.710	0.158	0.502	0.078
7	0.748	0.206	0.476	0.085	0.930	0.040	0.709	0.018
8	0.647	0.353	0.285	0.589	0.357	0.173	0.645	0.170
9	0.351	0.389	0.462	0.130	1.142	0.363	0.282	0.248
10(highest)	-0.163	0.667	0.265	0.401	-0.753	0.218	0.871	0.013

Table 3: Correlations of Skewness, Entropy Measures and Volatility

Panel A provides the time series average of the correlations of skewness, the entropy-based asymmetry measures and volatility from January 1962 to December 2013. Panel B provides the same correlations for the idiosyncratic measures.

Panel A: Total Measures				
	$SKEW$	E_φ	S_φ	VOL
$SKEW$	1.0000			
E_φ	-0.1233	1.0000		
S_φ	-0.0071	0.7051	1.0000	
VOL	0.0738	0.0312	0.0241	1.0000
Panel B: Idiosyncratic Measures				
	$ISKEW$	IE_φ	IS_φ	$IVOL$
$ISKEW$	1.0000			
IE_φ	-0.1649	1.0000		
IS_φ	-0.0342	0.6789	1.0000	
$IVOL$	0.0806	0.0610	0.0546	1.0000

Table 4: Firm Characteristics and Asymmetry Measures

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm characteristics (in the first column) on one of asymmetry measures from Columns (1)–(3), respectively. The characteristic variables are size ($SIZE$), book to market ratio (BM), momentum (MOM), turnover ($TURN$), liquidity measure ($ILLIQ$) and market beta (β). The slopes are scaled by 100. Significance at 1% and 5% levels are indicated by *** and **, respectively.

	(1)	(2)	(3)
VARIABLES	$ISKEW$	IE_φ	IS_φ
$SIZE$	-8.8554***	-0.0271***	-0.1108***
	(-23.78)	(-7.56)	(-9.64)
BM	-3.4407***	-0.0643***	-0.1931***
	(-6.04)	(-11.46)	(-11.73)
MOM	0.7705***	0.0014***	0.0081***
	(23.85)	(6.43)	(13.73)
$TURN$	-0.4458	0.1170***	0.2797***
	(-0.82)	(21.33)	(18.22)
$ILLIQ$	0.4324***	0.0036***	0.0120***
	(5.48)	(3.46)	(3.27)
β	3.0997**	0.0596***	0.3457***
	(2.53)	(6.10)	(9.78)
Constant	78.2001***	0.1945***	0.5875***
	(26.42)	(7.23)	(7.94)
R^2	0.103	0.028	0.020

Table 5: Fama-MacBeth Regressions

The table reports the slopes and their t-values of Fama-MacBeth regressions of firm excess returns on various pricing variables (in the first column) for monthly data from January 1962 to December 2013. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$ISKEW$	0.0113			0.0023	-0.0290*	-0.0247	-0.0191	0.0085	-0.0232	-0.0189	-0.0145
	(0.39)			(0.08)	(-1.66)	(-1.43)	(-1.08)	(0.27)	(-1.31)	(-1.08)	(-0.81)
IE_φ		-3.4598***		-3.7902***	-4.6618***	-4.6899***	-4.0147***				
		(-2.60)		(-2.66)	(-6.16)	(-6.16)	(-5.20)				
IS_φ			-0.8584***					-0.9046***	-1.1043***	-1.1022***	-0.9415***
			(-2.62)					(-2.78)	(-5.38)	(-5.35)	(-4.47)
$SIZE$					-0.2134***	-0.2128***	-0.2033***		-0.2168***	-0.2163***	-0.2062***
					(-5.34)	(-5.40)	(-5.12)		(-5.42)	(-5.48)	(-5.19)
BM					0.2891***	0.2899***	0.2438***		0.2864***	0.2871***	0.2418***
					(5.40)	(5.41)	(4.50)		(5.35)	(5.36)	(4.46)
MOM					0.0101***	0.0100***	0.0093***		0.0101***	0.0100***	0.0093***
					(6.84)	(6.79)	(5.94)		(6.78)	(6.72)	(5.91)
$TURN$					-0.0275	-0.0407	-0.0114		-0.0235	-0.0359	-0.0082
					(-0.77)	(-1.14)	(-0.32)		(-0.65)	(-1.00)	(-0.23)
$ILLIQ$					0.0113**	0.0090*	0.0114**		0.0115**	0.0093*	0.0115**
					(2.02)	(1.70)	(2.13)		(2.05)	(1.75)	(2.14)
β					0.9134***	0.8660***	0.7913***		0.9224***	0.8780***	0.8015***
					(4.51)	(4.37)	(3.90)		(4.55)	(4.43)	(3.95)
MAX					-0.0363***	-0.0538***	0.0294***		-0.0442***	-0.0614***	0.0229***
					(-3.46)	(-5.29)	(3.85)		(-4.16)	(-5.97)	(2.99)
VOL					-0.3618***				-0.3590***		
					(-8.86)				(-8.68)		
$IVOL$						-0.2892***	-0.4714***			-0.2884***	-0.4705***
						(-8.12)	(-15.55)			(-8.01)	(-15.44)
REV							-0.0383***				-0.0380***
							(-10.21)				(-10.12)
Constant	0.6564***	0.6771***	0.6759***	0.6698***	2.0986***	2.0658***	2.0427***	0.6661***	2.1265***	2.0963***	2.0691***
	(2.84)	(2.90)	(2.88)	(2.92)	(7.08)	(7.12)	(6.92)	(2.90)	(7.16)	(7.21)	(7.00)
R^2	0.003	0.002	0.001	0.005	0.088	0.088	0.093	0.004	0.088	0.088	0.093

Table 6: Fama-MacBeth Regression Using Risk-Adjusted Return as Dependent Variable

The table reports the slopes and their t-values of Fama-MacBeth regressions of firm risk-adjusted returns on various pricing variables (in the first column) for monthly data from January 1962 to December 2013. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$ISKEW$	-0.0218			-0.0298	-0.0238	-0.0244	-0.0235	-0.0281	-0.0173	-0.0181	-0.0188
	(-1.15)			(-1.52)	(-1.42)	(-1.47)	(-1.36)	(-1.39)	(-1.00)	(-1.06)	(-1.06)
IE_{φ}		-2.7588***		-3.2215***	-3.5363***	-3.5185***	-2.9227***				
		(-3.15)		(-3.52)	(-4.90)	(-4.84)	(-3.96)				
IS_{φ}			-0.6410***					-0.7295***	-0.7949***	-0.7838***	-0.6467***
			(-3.04)					(-3.33)	(-4.05)	(-3.99)	(-3.20)
$SIZE$					-0.1313***	-0.1330***	-0.1219***		-0.1324***	-0.1340***	-0.1230***
					(-10.01)	(-10.09)	(-9.11)		(-10.13)	(-10.21)	(-9.22)
BM					0.0731*	0.0693*	0.0126		0.0740*	0.0702*	0.0135
					(1.93)	(1.83)	(0.33)		(1.95)	(1.85)	(0.35)
MOM					0.0093***	0.0091***	0.0084***		0.0093***	0.0092***	0.0084***
					(6.73)	(6.62)	(5.76)		(6.67)	(6.55)	(5.71)
$TURN$					0.1299***	0.1324***	0.1412***		0.1331***	0.1364***	0.1446***
					(4.09)	(4.05)	(4.24)		(4.16)	(4.13)	(4.31)
$ILLIQ$					0.0131***	0.0141***	0.0177***		0.0132***	0.0142***	0.0178***
					(2.67)	(2.93)	(3.61)		(2.67)	(2.96)	(3.62)
MAX					-0.0823***	-0.0766***	0.0226***		-0.0881***	-0.0820***	0.0183**
					(-7.96)	(-8.17)	(2.98)		(-8.46)	(-8.66)	(2.37)
VOL					-0.1099***				-0.1049***		
					(-3.03)				(-2.86)		
$IVOL$						-0.1355***	-0.3603***			-0.1325***	-0.3588***
						(-4.11)	(-12.36)			(-3.97)	(-12.10)
$REVA$							-0.0475***				-0.0473***
							(-13.12)				(-13.02)
Constant	0.0639*	0.0643**	0.0613*	0.0750**	1.1943***	1.2227***	1.1147***	0.0710**	1.2082***	1.2380***	1.1301***
	(1.81)	(1.97)	(1.87)	(2.10)	(10.27)	(10.48)	(9.26)	(1.98)	(10.36)	(10.56)	(9.32)
R^2	0.002	0.001	0.001	0.003	0.031	0.031	0.036	0.003	0.031	0.031	0.037

Table 7: Decile Portfolios Sorted by $ISKEW$

The table reports the average returns and their t-values, as well as the CAPM Alpha denotes the average CAPM alpha and Fama-French 3-factor alpha for decile portfolios sorted by $ISKEW$ based on data from January 1962 to December 2013. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Portfolio	Monthly Excess Return (%)	CAPM Alpha (%)	FF3 Alpha (%)
1(lowest)	0.477***	-0.030	-0.216**
	(2.26)	(-0.32)	(-3.31)
2	0.660***	0.176**	-0.020
	(3.35)	(2.25)	(-0.39)
3	0.659***	0.173**	-0.033
	(3.32)	(2.17)	(-0.64)
4	0.687***	0.190**	-0.016
	(3.39)	(2.35)	(-0.32)
5	0.751***	0.241***	0.044
	(3.60)	(2.84)	(0.94)
6	0.782***	0.254***	0.035
	(3.58)	(2.73)	(0.75)
7	0.723***	0.182*	-0.018
	(3.20)	(1.82)	(-0.37)
8	0.735***	0.175	-0.030
	(3.12)	(1.62)	(-0.58)
9	0.659***	0.099	-0.094*
	(2.76)	(0.86)	(-1.80)
10(highest)	0.550**	0.047	-0.168***
	(2.48)	(0.40)	(-2.97)
10-1 spread	0.073	0.077	0.048
	(0.77)	(0.81)	(0.54)

Table 8: Decile Portfolios Sorted by IE_φ

The table reports the average returns and their t-values, as well as the CAPM Alpha denotes the average CAPM alpha and Fama-French 3-factor alpha for decile portfolios sorted by IE_φ based on data from January 1962 to December 2013. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Portfolio	Monthly Excess Return (%)	CAPM Alpha (%)	FF3 Alpha (%)
1(lowest)	0.694***	0.226**	-0.015
	(3.51)	(2.45)	(-0.29)
2	0.718***	0.217**	-0.008
	(3.46)	(2.44)	(-0.16)
3	0.713***	0.207**	-0.009
	(3.42)	(2.37)	(-0.19)
4	0.729***	0.217**	0.006
	(3.47)	(2.51)	(0.13)
5	0.706***	0.183**	-0.029
	(3.29)	(2.07)	(-0.64)
6	0.701***	0.173*	-0.030
	(3.24)	(1.96)	(-0.70)
7	0.623***	0.092	-0.096**
	(2.87)	(1.05)	(-2.23)
8	0.651***	0.119	-0.065
	(2.97)	(1.30)	(-1.55)
9	0.610***	0.072	-0.104**
	(2.73)	(0.74)	(-2.41)
10(highest)	0.515**	-0.021	-0.197***
	(2.28)	(-0.20)	(-4.09)
10-1 spread	-0.179**	-0.247***	-0.182***
	(-2.57)	(-3.77)	(-3.11)

Table 9: Decile Portfolios Sorted by IS_{φ}

The table reports the average returns and their t-values, as well as the CAPM Alpha denotes the average CAPM alpha and Fama-French 3-factor alpha for decile portfolios sorted by IS_{φ} based on data from January 1962 to December 2013. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Portfolio	Monthly Excess Return (%)	CAPM Alpha (%)	FF3 Alpha (%)
1(lowest)	0.768***	0.249**	0.026
	(3.51)	(2.45)	(0.49)
2	0.761***	0.255***	0.019
	(3.62)	(2.80)	(0.39)
3	0.702***	0.209**	-0.014
	(3.44)	(2.39)	(-0.28)
4	0.714***	0.232**	0.004
	(3.59)	(2.76)	(0.08)
5	0.631***	0.132	-0.057
	(3.10)	(1.60)	(-1.25)
6	0.607***	0.086	-0.109**
	(2.85)	(1.01)	(-2.49)
7	0.632***	0.108	-0.078*
	(2.94)	(1.21)	(-1.71)
8	0.651***	0.109	-0.081*
	(2.93)	(1.18)	(-1.82)
9	0.631***	0.081	-0.097**
	(2.78)	(0.84)	(-2.18)
10(highest)	0.575**	0.023	-0.162***
	(2.45)	(0.21)	(-3.09)
10-1 spread	-0.193***	-0.226***	-0.188***
	(-3.42)	(-4.08)	(-3.58)

Table 10: Fama-MacBeth Return Regressions on $ISKEW$ in VIX Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $ISKEW$ and other stock characteristic variables (in the first column) for monthly data from January 1962 to December 2013 in high and low VIX periods. Columns (1)–(4) are those in high periods when the previous month VIX is above its mean, and Columns (5)–(8) are those in low periods when the previous month VIX is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ISKEW$	-0.1393***	-0.0874***	-0.0816**	-0.0794**	0.0637**	0.0369**	0.0060	0.0112
	(-2.63)	(-2.67)	(-2.36)	(-2.35)	(2.13)	(2.22)	(0.34)	(0.65)
$SIZE$		-0.2251***	-0.2593***	-0.2556***		-0.1527***	-0.1951***	-0.1956***
		(-2.97)	(-3.39)	(-3.42)		(-4.13)	(-5.23)	(-5.30)
BM		0.2850**	0.2826**	0.2824**		0.3082***	0.2975***	0.2988***
		(2.47)	(2.42)	(2.43)		(6.71)	(6.43)	(6.46)
MOM		0.0013	0.0018	0.0019		0.0122***	0.0128***	0.0127***
		(0.33)	(0.48)	(0.49)		(8.92)	(9.36)	(9.23)
$TURN$		0.1808**	0.1539*	0.1462*		-0.1350***	-0.1005***	-0.1159***
		(2.42)	(1.96)	(1.90)		(-4.26)	(-3.14)	(-3.58)
$ILLIQ$		-0.0400***	-0.0396***	-0.0392***		0.0075*	0.0290***	0.0258***
		(-3.80)	(-3.50)	(-3.60)		(1.67)	(5.85)	(5.24)
β		0.7968*	0.8791*	0.8675*		0.7522***	0.9237***	0.8628***
		(1.69)	(1.83)	(1.82)		(4.63)	(5.52)	(5.18)
MAX		-0.1105***	-0.0934***	-0.1020***		-0.1211***	-0.0152	-0.0362***
		(-10.00)	(-5.16)	(-5.43)		(-19.10)	(-1.47)	(-3.51)
VOL			-0.0974				-0.4593***	
			(-1.37)				(-11.77)	
$IVOL$				-0.0635				-0.3717***
				(-0.99)				(-10.01)
Constant	1.2943***	2.7956***	3.0738***	3.0339***	0.4346*	1.2860***	1.7434***	1.7126***
	(2.72)	(5.16)	(5.51)	(5.59)	(1.91)	(4.75)	(6.31)	(6.30)
R^2	0.003	0.109	0.112	0.112	0.003	0.076	0.079	0.079

Table 11: Fama-MacBeth Return Regressions on IE_φ in VIX Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on IE_φ and other stock characteristic variables (in the first column) for monthly data from January 1962 to December 2013 in high and low VIX periods. Columns (1)–(4) are those in high periods when the previous month VIX is above its mean, and Columns (5)–(8) are those in low periods when the previous month VIX is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IE_φ	-4.9582	-6.4421***	-6.4724***	-6.3326***	-2.9387***	-3.9268***	-3.3202***	-3.4426***
	(-1.35)	(-3.69)	(-3.61)	(-3.53)	(-2.60)	(-5.39)	(-4.49)	(-4.64)
$SIZE$		-0.2224***	-0.2526***	-0.2497***		-0.1588***	-0.1974***	-0.1981***
		(-2.94)	(-3.31)	(-3.35)		(-4.26)	(-5.26)	(-5.33)
BM		0.2833**	0.2825**	0.2814**		0.3060***	0.2945***	0.2957***
		(2.45)	(2.41)	(2.42)		(6.65)	(6.37)	(6.39)
MOM		0.0006	0.0013	0.0013		0.0125***	0.0128***	0.0127***
		(0.16)	(0.34)	(0.35)		(9.19)	(9.53)	(9.41)
$TURN$		0.1959***	0.1662**	0.1595**		-0.1355***	-0.0969***	-0.1122***
		(2.63)	(2.14)	(2.10)		(-4.27)	(-3.03)	(-3.47)
$ILLIQ$		-0.0394***	-0.0394***	-0.0386***		0.0072	0.0283***	0.0252***
		(-3.75)	(-3.48)	(-3.55)		(1.62)	(5.76)	(5.16)
β		0.7831*	0.8491*	0.8461*		0.7616***	0.9219***	0.8622***
		(1.66)	(1.77)	(1.77)		(4.65)	(5.51)	(5.16)
MAX		-0.1130***	-0.1013***	-0.1081***		-0.1205***	-0.0171*	-0.0373***
		(-10.11)	(-5.70)	(-5.78)		(-19.02)	(-1.69)	(-3.70)
VOL			-0.0737				-0.4525***	
			(-1.07)				(-11.81)	
$IVOL$				-0.0474				-0.3672***
				(-0.75)				(-10.02)
Constant	1.2530***	2.7706***	3.0079***	2.9765***	0.4769**	1.3346***	1.7577***	1.7306***
	(2.65)	(5.14)	(5.44)	(5.53)	(2.07)	(4.91)	(6.36)	(6.35)
R^2	0.002	0.108	0.111	0.111	0.001	0.075	0.078	0.078

Table 12: Fama-MacBeth Return Regressions on IS_φ in VIX Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on IS_φ and other stock characteristic variables (in the first column) for monthly data from January 1962 to December 2013 in high and low VIX periods. Columns (1)–(4) are those in high periods when the previous month VIX is above its mean, and Columns (5)–(8) are those in low periods when the previous month VIX is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS_φ	-1.7662*	-1.7107***	-1.6969***	-1.6440***	-0.5427**	-0.9267***	-0.8219***	-0.8378***
	(-1.88)	(-3.67)	(-3.53)	(-3.40)	(-2.13)	(-4.60)	(-3.96)	(-4.03)
$SIZE$		-0.2310***	-0.2577***	-0.2555***		-0.1632***	-0.2013***	-0.2020***
		(-3.05)	(-3.39)	(-3.44)		(-4.34)	(-5.35)	(-5.42)
BM		0.2739**	0.2734**	0.2722**		0.3046***	0.2928***	0.2941***
		(2.37)	(2.34)	(2.34)		(6.61)	(6.33)	(6.35)
MOM		0.0008	0.0015	0.0015		0.0125***	0.0128***	0.0127***
		(0.20)	(0.40)	(0.40)		(9.16)	(9.48)	(9.37)
$TURN$		0.1993***	0.1733**	0.1689**		-0.1349***	-0.0930***	-0.1081***
		(2.63)	(2.21)	(2.20)		(-4.21)	(-2.88)	(-3.32)
$ILLIQ$		-0.0390***	-0.0386***	-0.0375***		0.0075*	0.0284***	0.0253***
		(-3.69)	(-3.38)	(-3.42)		(1.65)	(5.72)	(5.13)
β		0.8103*	0.8522*	0.8615*		0.7810***	0.9333***	0.8733***
		(1.71)	(1.77)	(1.80)		(4.74)	(5.56)	(5.22)
MAX		-0.1225***	-0.1110***	-0.1166***		-0.1273***	-0.0239**	-0.0441***
		(-10.59)	(-6.11)	(-6.16)		(-19.50)	(-2.35)	(-4.35)
VOL			-0.0703				-0.4511***	
			(-0.99)				(-11.71)	
$IVOL$				-0.0515				-0.3661***
				(-0.80)				(-9.94)
Constant	1.2563***	2.8375***	3.0502***	3.0285***	0.4740**	1.3724***	1.7903***	1.7637***
	(2.65)	(5.24)	(5.52)	(5.64)	(2.05)	(4.99)	(6.45)	(6.44)
R^2	0.002	0.109	0.112	0.112	0.001	0.076	0.079	0.079

Table 13: Fama-MacBeth Return Regressions on $ISKEW$ for different $IVOL$ Levels

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $ISKEW$ and other stock characteristic variables (in the first column) for monthly data from January 1962 to December 2013 for high and low $IVOL$ stocks separately. Columns (1)–(4) are those stocks with high $IVOL$ which the previous month $IVOL$ is above its cross-sectional mean, and Columns (5)–(8) are those stocks with low $IVOL$ which the previous month $IVOL$ is below its cross-sectional mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ISKEW$	-0.0411	-0.1246***	-0.0059	0.0256	0.1010***	-0.0149	-0.0037	-0.0056
	(-1.55)	(-5.47)	(-0.26)	(1.10)	(4.44)	(-0.93)	(-0.23)	(-0.35)
$SIZE$		-0.2320***	-0.2278***	-0.2096***		-0.1806***	-0.1988***	-0.1689***
		(-5.46)	(-5.34)	(-5.04)		(-5.45)	(-6.00)	(-5.26)
BM		0.3768***	0.3509***	0.3160***		0.2600***	0.2333***	0.1968***
		(7.45)	(6.95)	(6.38)		(5.61)	(5.06)	(4.30)
MOM		0.0127***	0.0111***	0.0104***		0.0089***	0.0082***	0.0080***
		(8.78)	(7.51)	(6.96)		(5.32)	(4.90)	(4.78)
$TURN$		-0.2665***	-0.1358***	-0.1442***		-0.0231	0.0337	0.0382
		(-7.31)	(-3.59)	(-3.97)		(-0.75)	(1.11)	(1.29)
$ILLIQ$		-0.0173***	-0.0106**	-0.0112**		-0.0016	0.0025	-0.0011
		(-3.32)	(-2.07)	(-2.21)		(-0.27)	(0.43)	(-0.18)
β		0.8490***	0.8710***	0.8394***		0.6537***	0.8050***	0.6285***
		(5.16)	(5.30)	(5.16)		(3.59)	(4.34)	(3.46)
MAX			-0.0840***	-0.0645***			-0.1421***	-0.0435***
			(-13.95)	(-10.65)			(-13.94)	(-4.20)
REV				-0.0208***				-0.0544***
				(-6.26)				(-13.67)
Constant	0.4253*	1.2539***	1.6069***	1.4239***	0.8207***	1.4001***	1.8275***	1.4721***
	(1.66)	(4.43)	(5.62)	(5.13)	(4.39)	(5.67)	(7.27)	(6.06)
R^2	0.003	0.073	0.076	0.082	0.003	0.086	0.089	0.095

Table 14: Fama-MacBeth Return Regressions on IE_φ for different $IVOL$ Levels

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on IE_φ and other stock characteristic variables (in the first column) for monthly data from January 1962 to December 2013 for high and low $IVOL$ stocks separately. Columns (1)–(4) are those stocks with high $IVOL$ which the previous month $IVOL$ is above its cross-sectional mean, and Columns (5)–(8) are those stocks with low $IVOL$ which the previous month $IVOL$ is below its cross-sectional mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IE_φ	-4.7171***	-6.1111***	-6.9106***	-6.7578***	-0.6338	-2.4602***	-2.3086***	-1.8579**
	(-3.25)	(-5.35)	(-6.03)	(-5.96)	(-0.66)	(-3.32)	(-3.12)	(-2.54)
$SIZE$		-0.2202***	-0.2291***	-0.2142***		-0.1810***	-0.1999***	-0.1700***
		(-5.14)	(-5.34)	(-5.11)		(-5.46)	(-6.03)	(-5.29)
BM		0.3780***	0.3487***	0.3135***		0.2590***	0.2332***	0.1968***
		(7.42)	(6.87)	(6.30)		(5.59)	(5.06)	(4.30)
MOM		0.0121***	0.0111***	0.0107***		0.0087***	0.0081***	0.0078***
		(8.27)	(7.53)	(7.25)		(5.22)	(4.86)	(4.74)
$TURN$		-0.2617***	-0.1283***	-0.1413***		-0.0217	0.0340	0.0383
		(-7.16)	(-3.38)	(-3.88)		(-0.71)	(1.13)	(1.29)
$ILLIQ$		-0.0178***	-0.0108**	-0.0114**		-0.0022	0.0019	-0.0018
		(-3.41)	(-2.09)	(-2.25)		(-0.38)	(0.32)	(-0.31)
β		0.8450***	0.8729***	0.8442***		0.6509***	0.8016***	0.6238***
		(5.09)	(5.26)	(5.14)		(3.59)	(4.34)	(3.44)
MAX			-0.0852***	-0.0641***			-0.1409***	-0.0424***
			(-14.46)	(-10.76)			(-13.74)	(-4.07)
REV				-0.0203***				-0.0544***
				(-6.16)				(-13.65)
Constant	0.4191	1.1759***	1.6509***	1.4856***	0.8652***	1.3996***	1.8316***	1.4762***
	(1.65)	(4.15)	(5.75)	(5.32)	(4.62)	(5.69)	(7.30)	(6.10)
R^2	0.002	0.073	0.076	0.082	0.001	0.086	0.088	0.095

Table 15: Fama-MacBeth Return Regressions on IS_{φ} for different $IVOL$ Levels

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on IS_{φ} and other stock characteristic variables (in the first column) for monthly data from January 1962 to December 2013 for high and low $IVOL$ stocks separately. Columns (1)–(4) are those stocks with high $IVOL$ which the previous month $IVOL$ is above its cross-sectional mean, and Columns (5)–(8) are those stocks with low $IVOL$ which the previous month $IVOL$ is below its cross-sectional mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS_{φ}	-1.2355***	-1.5997***	-1.6957***	-1.6022***	0.0140	-0.4784**	-0.4258*	-0.3566*
	(-3.51)	(-5.33)	(-5.63)	(-5.35)	(0.05)	(-2.20)	(-1.96)	(-1.66)
$SIZE$		-0.2209***	-0.2332***	-0.2176***		-0.1803***	-0.1998***	-0.1698***
		(-5.10)	(-5.37)	(-5.13)		(-5.43)	(-6.00)	(-5.27)
BM		0.3758***	0.3444***	0.3101***		0.2593***	0.2331***	0.1965***
		(7.34)	(6.75)	(6.20)		(5.59)	(5.05)	(4.29)
MOM		0.0122***	0.0111***	0.0107***		0.0088***	0.0082***	0.0079***
		(8.35)	(7.55)	(7.27)		(5.22)	(4.86)	(4.73)
$TURN$		-0.2646***	-0.1253***	-0.1395***		-0.0233	0.0330	0.0375
		(-7.10)	(-3.24)	(-3.76)		(-0.75)	(1.09)	(1.26)
$ILLIQ$		-0.0173***	-0.0103**	-0.0110**		-0.0021	0.0021	-0.0017
		(-3.29)	(-1.98)	(-2.14)		(-0.35)	(0.35)	(-0.28)
β		0.8574***	0.8931***	0.8638***		0.6488***	0.8021***	0.6239***
		(5.14)	(5.35)	(5.23)		(3.57)	(4.33)	(3.43)
MAX			-0.0926***	-0.0707***			-0.1433***	-0.0444***
			(-15.18)	(-11.49)			(-13.97)	(-4.25)
REV				-0.0200***				-0.0545***
				(-6.04)				(-13.69)
Constant	0.4148	1.1613***	1.6957***	1.5208***	0.8633***	1.3974***	1.8376***	1.4811***
	(1.62)	(4.03)	(5.79)	(5.35)	(4.61)	(5.66)	(7.30)	(6.09)
R^2	0.002	0.073	0.076	0.082	0.001	0.086	0.088	0.095

Table 16: Portfolio Sorted by $IVOL$ and Asymmetry Measures

The table reports the average returns and their t-values for quintile portfolios sorted by $IVOL$ and then by $ISKEW$, IE_φ or IS_φ based on monthly data from January 1962 to December 2013. $IVOL1$ and $IVOL5$ denote the lowest and highest quintiles for $IVOL$, and $P1$ and $P5$ denote the lowest and highest quintiles for $ISKEW$, IE_φ and IS_φ, respectively. Significance at 1% and 5% levels are indicated by *** and **, respectively.

	$ISKEW$			IE_φ			IS_φ		
Proxy	P1	P5	P5-P1	P1	P5	P5-P1	P1	P5	P5-P1
$IVOL1$	0.587***	0.843***	0.257***	0.713***	0.779***	0.066	0.757***	0.790***	0.033
t-stat	(3.67)	(5.33)	(4.13)	(4.65)	(4.90)	(1.49)	(4.90)	(4.99)	(0.80)
$IVOL2$	0.812***	1.112***	0.300***	0.964***	0.887***	-0.077	1.030***	0.910***	-0.120**
t-stat	(4.23)	(5.47)	(4.15)	(5.07)	(4.60)	(-1.45)	(5.26)	(4.59)	(-2.37)
$IVOL3$	0.787***	0.963***	0.176**	0.989***	0.870***	-0.119*	1.029***	0.994***	-0.035
t-stat	(3.53)	(4.09)	(2.09)	(4.52)	(3.82)	(-1.83)	(4.54)	(4.24)	(-0.55)
$IVOL4$	0.661***	0.775***	0.114	0.821***	0.714***	-0.107	0.943***	0.701***	-0.242***
t-stat	(2.58)	(2.92)	(1.23)	(3.35)	(2.70)	(-1.51)	(3.68)	(2.64)	(-3.58)
$IVOL5$	0.067	-0.073	-0.140	0.119	-0.086	-0.206**	0.196	-0.019	-0.216***
t-stat	(0.23)	(-0.26)	(-1.22)	(0.43)	(-0.29)	(-2.30)	(0.69)	(-0.06)	(-2.62)
Avg(V1-V5)	0.583***	0.724***	0.141**	0.721***	0.633***	-0.089**	0.791***	0.675***	-0.116***
t-stat	(2.69)	(3.28)	(2.33)	(3.45)	(2.88)	(-2.27)	(3.67)	(3.03)	(-3.45)

Table 17: Fama-MacBeth Return Regressions on $ISKEW$ in Sentiment Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $ISKEW$ and other stock characteristic variables (in the first column) for monthly data from August 1965 to December 2013 in high and low sentiment periods. Columns (1)–(4) are those in high periods when the previous month sentiment is one standard deviation above its mean, and Columns (5)–(8) are those in low periods when the previous month sentiment is one standard deviation below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ISKEW$	-0.2035**	-0.0901*	-0.1129**	-0.1058*	0.1549*	0.1377***	0.1390***	0.1384***
	(-2.52)	(-1.84)	(-2.07)	(-1.97)	(1.71)	(3.29)	(3.12)	(3.09)
$SIZE$		-0.1053	-0.1447	-0.1432		-0.3914***	-0.3942***	-0.3900***
		(-1.11)	(-1.51)	(-1.52)		(-3.57)	(-3.63)	(-3.66)
BM		0.4230***	0.4191***	0.4187***		0.4553***	0.4543***	0.4536***
		(3.54)	(3.47)	(3.48)		(2.70)	(2.67)	(2.68)
MOM		0.0159***	0.0160***	0.0160***		0.0023	0.0033	0.0032
		(3.68)	(3.78)	(3.76)		(0.49)	(0.68)	(0.68)
$TURN$		0.1248	0.1401	0.1196		-0.0675	-0.0688	-0.0777
		(1.49)	(1.65)	(1.42)		(-0.69)	(-0.66)	(-0.73)
$ILLIQ$		-0.0139	-0.0012	-0.0049		-0.0242**	-0.0082	-0.0102
		(-1.10)	(-0.09)	(-0.38)		(-2.55)	(-0.77)	(-0.92)
β		-0.3780	-0.2258	-0.3175		1.4921***	1.5290***	1.5029***
		(-0.72)	(-0.44)	(-0.61)		(3.27)	(3.33)	(3.29)
MAX		-0.1584***	-0.0896***	-0.1073***		-0.1614***	-0.1241***	-0.1357***
		(-10.72)	(-3.44)	(-4.17)		(-10.90)	(-4.16)	(-4.19)
VOL			-0.3035***				-0.1729	
			(-2.96)				(-1.57)	
$IVOL$				-0.2280**				-0.1193
				(-2.27)				(-1.01)
Constant	-0.1124	1.9272***	2.3542***	2.3271***	0.9159	2.2085***	2.2893***	2.2410***
	(-0.18)	(2.88)	(3.36)	(3.38)	(1.34)	(2.80)	(2.94)	(2.99)
R^2	0.004	0.110	0.113	0.113	0.005	0.109	0.112	0.112

Table 18: Fama-MacBeth Return Regressions on IE_φ in Sentiment Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on IE_φ and other stock characteristic variables (in the first column) for monthly data from August 1965 to December 2013 in high and low sentiment periods. Columns (1)–(4) are those in high periods when the previous month sentiment is one standard deviation above its mean, and Columns (5)–(8) are those in low periods when the previous month sentiment is one standard deviation below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IE_φ	-8.6049**	-4.3564**	-3.6382*	-3.8058*	-0.3313	-3.6942*	-3.1468	-3.1975
	(-2.21)	(-2.16)	(-1.71)	(-1.80)	(-0.10)	(-1.67)	(-1.41)	(-1.43)
$SIZE$		-0.0999	-0.1338	-0.1323		-0.4033***	-0.4079***	-0.4039***
		(-1.05)	(-1.39)	(-1.40)		(-3.67)	(-3.74)	(-3.78)
BM		0.4250***	0.4247***	0.4237***		0.4545***	0.4532***	0.4521***
		(3.55)	(3.51)	(3.52)		(2.70)	(2.66)	(2.67)
MOM		0.0153***	0.0154***	0.0154***		0.0035	0.0044	0.0043
		(3.58)	(3.68)	(3.66)		(0.72)	(0.91)	(0.91)
$TURN$		0.1368	0.1497*	0.1317		-0.0734	-0.0741	-0.0833
		(1.64)	(1.77)	(1.57)		(-0.76)	(-0.73)	(-0.79)
$ILLIQ$		-0.0143	-0.0025	-0.0059		-0.0236**	-0.0071	-0.0091
		(-1.13)	(-0.19)	(-0.46)		(-2.57)	(-0.68)	(-0.84)
β		-0.3754	-0.2398	-0.3244		1.4834***	1.5309***	1.4975***
		(-0.71)	(-0.46)	(-0.62)		(3.26)	(3.34)	(3.28)
MAX		-0.1647***	-0.1038***	-0.1198***		-0.1521***	-0.1096***	-0.1220***
		(-11.00)	(-4.21)	(-4.92)		(-10.82)	(-3.90)	(-3.96)
VOL			-0.2739***				-0.1958*	
			(-2.78)				(-1.82)	
$IVOL$				-0.2052**				-0.1393
				(-2.11)				(-1.19)
Constant	-0.2001	1.8875***	2.2583***	2.2345***	0.9875	2.2850***	2.3864***	2.3385***
	(-0.32)	(2.82)	(3.25)	(3.27)	(1.41)	(2.89)	(3.06)	(3.12)
R^2	0.002	0.110	0.112	0.113	0.002	0.108	0.111	0.112

Table 19: Fama-MacBeth Return Regressions on IS_{φ} in Sentiment Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on IS_{φ} and other stock characteristic variables (in the first column) for monthly data from August 1965 to December 2013 in high and low sentiment periods. Columns (1)–(4) are those in high periods when the previous month sentiment is one standard deviation above its mean, and Columns (5)–(8) are those in low periods when the previous month sentiment is one standard deviation below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS_{φ}	-2.6933***	-1.6846***	-1.6471***	-1.6513***	-0.2283	-0.8868	-0.8574	-0.8640
	(-3.04)	(-3.25)	(-3.02)	(-3.03)	(-0.27)	(-1.47)	(-1.43)	(-1.43)
$SIZE$		-0.1078	-0.1389	-0.1379		-0.4090***	-0.4143***	-0.4107***
		(-1.12)	(-1.44)	(-1.45)		(-3.71)	(-3.78)	(-3.82)
BM		0.4235***	0.4213***	0.4202***		0.4519***	0.4510***	0.4500***
		(3.52)	(3.47)	(3.47)		(2.68)	(2.65)	(2.66)
MOM		0.0153***	0.0154***	0.0154***		0.0032	0.0041	0.0041
		(3.56)	(3.66)	(3.64)		(0.67)	(0.86)	(0.86)
$TURN$		0.1407*	0.1596*	0.1426*		-0.0655	-0.0643	-0.0723
		(1.67)	(1.87)	(1.69)		(-0.66)	(-0.62)	(-0.68)
$ILLIQ$		-0.0148	-0.0027	-0.0059		-0.0229**	-0.0068	-0.0086
		(-1.16)	(-0.20)	(-0.46)		(-2.50)	(-0.65)	(-0.80)
β		-0.3576	-0.2278	-0.3088		1.5005***	1.5476***	1.5146***
		(-0.67)	(-0.44)	(-0.59)		(3.28)	(3.37)	(3.31)
MAX		-0.1750***	-0.1158***	-0.1308***		-0.1602***	-0.1201***	-0.1316***
		(-11.31)	(-4.69)	(-5.34)		(-11.31)	(-4.25)	(-4.26)
VOL			-0.2642***				-0.1885*	
			(-2.69)				(-1.75)	
$IVOL$				-0.2012**				-0.1374
				(-2.06)				(-1.18)
Constant	-0.1979	1.9686***	2.3066***	2.2887***	0.9950	2.3401***	2.4452***	2.4038***
	(-0.31)	(2.90)	(3.30)	(3.33)	(1.41)	(2.96)	(3.13)	(3.20)
R^2	0.001	0.110	0.113	0.113	0.002	0.109	0.112	0.112

Table 20: Fama-MacBeth Regressions on $ISKEW$ in $ALIQ$ Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on $ISKEW$ and other stock characteristic variables (in the first column) for monthly data from September 1962 to December 2013 in high and low $ALIQ$ periods. Columns (1)–(4) are those in high periods when the previous month $ALIQ$ is above its mean, and Columns (5)–(8) are those in low periods when the previous month $ALIQ$ is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ISKEW$	0.0665*	0.0096	-0.0169	-0.0128	-0.0611	0.0050	-0.0112	-0.0047
	(1.96)	(0.51)	(-0.87)	(-0.66)	(-1.46)	(0.20)	(-0.42)	(-0.18)
$SIZE$		-0.1836***	-0.2273***	-0.2299***		-0.1575***	-0.1952***	-0.1891***
		(-4.43)	(-5.49)	(-5.63)		(-2.75)	(-3.35)	(-3.30)
BM		0.2575***	0.2499***	0.2498***		0.3549***	0.3436***	0.3469***
		(4.81)	(4.62)	(4.63)		(4.52)	(4.35)	(4.41)
MOM		0.0117***	0.0122***	0.0121***		0.0056**	0.0062**	0.0061**
		(7.64)	(7.95)	(7.87)		(2.07)	(2.35)	(2.33)
$TURN$		-0.1200***	-0.1045***	-0.1146***		0.0434	0.0677	0.0489
		(-3.13)	(-2.70)	(-2.97)		(0.84)	(1.28)	(0.92)
$ILLIQ$		0.0060	0.0261***	0.0242***		-0.0211***	-0.0102	-0.0137*
		(1.07)	(4.18)	(3.94)		(-3.15)	(-1.40)	(-1.90)
β		1.0036***	1.1819***	1.1400***		0.4818	0.6003*	0.5361*
		(5.17)	(5.96)	(5.73)		(1.56)	(1.90)	(1.71)
MAX		-0.1142***	-0.0207*	-0.0338***		-0.1252***	-0.0520***	-0.0786***
		(-16.06)	(-1.77)	(-2.97)		(-14.42)	(-3.64)	(-5.32)
VOL			-0.4104***				-0.3254***	
			(-9.18)				(-5.90)	
$IVOL$				-0.3571***				-0.2119***
				(-8.55)				(-4.06)
Constant	0.8773***	1.7004***	2.1553***	2.1439***	0.4499	1.7155***	2.0913***	2.0128***
	(3.80)	(5.87)	(7.39)	(7.47)	(1.18)	(3.96)	(4.68)	(4.60)
R^2	0.003	0.073	0.076	0.076	0.003	0.098	0.101	0.101

Table 21: Fama-MacBeth Regressions on IE_φ in $ALIQ$ Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on IE_φ and other stock characteristic variables (in the first column) for monthly data from September 1962 to December 2013 in high and low $ALIQ$ periods. Columns (1)–(4) are those in high periods when the previous month $ALIQ$ is above its mean, and Columns (5)–(8) are those in low periods when the previous month $ALIQ$ is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IE_φ	-2.6684*	-4.7573***	-4.4286***	-4.5072***	-4.5150**	-4.4679***	-3.8375***	-3.9185***
	(-1.75)	(-5.44)	(-4.96)	(-5.06)	(-2.07)	(-3.76)	(-3.18)	(-3.23)
$SIZE$		-0.1892***	-0.2283***	-0.2311***		-0.1595***	-0.1941***	-0.1886***
		(-4.54)	(-5.49)	(-5.62)		(-2.78)	(-3.33)	(-3.29)
BM		0.2554***	0.2466***	0.2463***		0.3528***	0.3427***	0.3457***
		(4.76)	(4.55)	(4.55)		(4.49)	(4.34)	(4.39)
MOM		0.0117***	0.0120***	0.0120***		0.0056**	0.0062**	0.0062**
		(7.76)	(8.01)	(7.93)		(2.09)	(2.34)	(2.33)
$TURN$		-0.1172***	-0.0977**	-0.1075***		0.0473	0.0723	0.0537
		(-3.04)	(-2.53)	(-2.79)		(0.92)	(1.38)	(1.02)
$ILLIQ$		0.0058	0.0255***	0.0237***		-0.0210***	-0.0103	-0.0136*
		(1.04)	(4.10)	(3.88)		(-3.15)	(-1.42)	(-1.91)
β		1.0150***	1.1751***	1.1374***		0.4777	0.5914*	0.5286*
		(5.19)	(5.92)	(5.71)		(1.54)	(1.87)	(1.69)
MAX		-0.1152***	-0.0256**	-0.0377***		-0.1242***	-0.0532***	-0.0787***
		(-16.10)	(-2.23)	(-3.36)		(-14.33)	(-3.83)	(-5.41)
VOL			-0.3970***				-0.3183***	
			(-8.98)				(-5.93)	
$IVOL$				-0.3470***				-0.2083***
				(-8.37)				(-4.06)
Constant	0.9247***	1.7460***	2.1593***	2.1511***	0.4354	1.7260***	2.0728***	2.0010***
	(3.97)	(6.01)	(7.39)	(7.47)	(1.13)	(3.99)	(4.67)	(4.60)
R^2	0.001	0.073	0.076	0.076	0.002	0.098	0.101	0.100

Table 22: Fama-MacBeth Regressions on IS_φ in $ALIQ$ Regimes

The table reports the average slopes and their t-values of Fama-MacBeth regressions of firm excess returns on IS_φ and other stock characteristic variables (in the first column) for monthly data from September 1962 to December 2013 in high and low $ALIQ$ periods. Columns (1)–(4) are those in high periods when the previous month $ALIQ$ is above its mean, and Columns (5)–(8) are those in low periods when the previous month $ALIQ$ is below its mean. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	High				Low			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS_φ	-0.5461	-1.1749***	-1.0838***	-1.0931***	-1.3455**	-1.1076***	-1.0322***	-1.0230***
	(-1.52)	(-4.90)	(-4.42)	(-4.45)	(-2.47)	(-3.47)	(-3.12)	(-3.07)
$SIZE$		-0.1937***	-0.2313***	-0.2342***		-0.1666***	-0.2002***	-0.1950***
		(-4.62)	(-5.55)	(-5.70)		(-2.88)	(-3.43)	(-3.39)
BM		0.2556***	0.2468***	0.2465***		0.3442***	0.3339***	0.3370***
		(4.76)	(4.55)	(4.55)		(4.38)	(4.23)	(4.29)
MOM		0.0118***	0.0121***	0.0120***		0.0057**	0.0063**	0.0062**
		(7.75)	(7.99)	(7.90)		(2.09)	(2.35)	(2.34)
$TURN$		-0.1160***	-0.0937**	-0.1031***		0.0489	0.0779	0.0603
		(-2.97)	(-2.40)	(-2.65)		(0.94)	(1.47)	(1.14)
$ILLIQ$		0.0065	0.0256***	0.0239***		-0.0212***	-0.0101	-0.0132*
		(1.14)	(4.09)	(3.88)		(-3.16)	(-1.38)	(-1.84)
β		1.0337***	1.1811***	1.1445***		0.5036	0.6054*	0.5489*
		(5.26)	(5.94)	(5.74)		(1.62)	(1.90)	(1.75)
MAX		-0.1218***	-0.0320***	-0.0438***		-0.1330***	-0.0625***	-0.0876***
		(-16.47)	(-2.76)	(-3.88)		(-14.90)	(-4.42)	(-5.96)
VOL			-0.3949***				-0.3160***	
			(-8.87)				(-5.80)	
$IVOL$				-0.3462***				-0.2094***
				(-8.30)				(-4.05)
Constant	0.9231***	1.7819***	2.1848***	2.1782***	0.4348	1.7848***	2.1214***	2.0536***
	(3.94)	(6.08)	(7.46)	(7.55)	(1.13)	(4.08)	(4.77)	(4.71)
R^2	0.001	0.073	0.076	0.076	0.002	0.098	0.101	0.101

Table 23: Fama-MacBeth Return Regressions on $ISKEW$ and DUM_CGO

The table reports the slopes and their t-values of Fama-MacBeth regressions,

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}DUM\_CGO_{i,t} + \lambda_{3,t}ISKEW_{i,t} + \lambda_{4,t}DUM\_CGO_{i,t} \times ISKEW_{i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

where $X_{i,t}$ is a vector of other firm characteristics. The regressions are run for monthly data from January 1962 to December 2013. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
DUM_CGO	0.3216***	0.2879***	0.2812***	0.1992***	0.1600***	0.1368***
	(3.72)	(3.33)	(3.26)	(4.03)	(3.27)	(2.87)
$ISKEW$			-0.0357	-0.1283***	-0.0539**	-0.0638***
			(-1.07)	(-5.86)	(-2.51)	(-2.90)
$DUM\_CGO \times ISKEW$		0.0457*	0.0814***	0.0845***	0.0993***	0.1007***
		(1.70)	(3.06)	(3.26)	(3.83)	(3.82)
$SIZE$				-0.1508***	-0.1891***	-0.2125***
				(-4.05)	(-5.00)	(-5.60)
BM				0.3162***	0.2710***	0.2658***
				(6.16)	(5.29)	(5.16)
MOM				0.0085***	0.0069***	0.0074***
				(5.77)	(4.66)	(5.00)
$TURN$				-0.1884***	-0.0361	-0.0372
				(-4.82)	(-0.96)	(-1.00)
$ILLIQ$				-0.0129**	0.0006	0.0116*
				(-2.51)	(0.11)	(1.94)
β				0.6496***	0.7807***	0.8410***
				(3.40)	(4.01)	(4.27)
MAX					-0.1157***	-0.0730***
					(-16.20)	(-7.17)
$IVOL$						-0.1932***
						(-5.57)
Constant	0.5751**	0.5710**	0.5777**	1.2333***	1.6593***	1.9124***
	(2.43)	(2.43)	(2.50)	(4.43)	(5.82)	(6.68)
R^2	0.008	0.010	0.012	0.087	0.090	0.093

Table 24: Fama-MacBeth Return Regressions on IE_φ and DUM_CGO

The table reports the slopes and their t-values of Fama-MacBeth regressions,

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}DUM\_CGO_{i,t} + \lambda_{3,t}IE_{\varphi i,t} + \lambda_{4,t}DUM\_CGO_{i,t} \times IE_{\varphi i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

where $X_{i,t}$ is a vector containing other firm characteristics. The regressions are run for monthly data from January 1962 to December 2013. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
DUM_CGO	0.3216***	0.3191***	0.3035***	0.2260***	0.1946***	0.1725***
	(3.72)	(3.76)	(3.56)	(4.80)	(4.14)	(3.74)
IE_φ			-4.6120***	-6.1397***	-5.3802***	-5.0475***
			(-3.18)	(-5.62)	(-4.95)	(-4.57)
$DUM\_CGO \times IE_\varphi$		-2.5787	2.0333	2.1005	2.1755	2.4783
		(-1.56)	(1.20)	(1.25)	(1.29)	(1.46)
$ISKEW$				-0.1060***	-0.0224	-0.0292*
				(-6.20)	(-1.36)	(-1.72)
$SIZE$				-0.1533***	-0.1908***	-0.2134***
				(-4.11)	(-5.04)	(-5.61)
BM				0.3128***	0.2688***	0.2639***
				(6.12)	(5.26)	(5.13)
MOM				0.0086***	0.0070***	0.0075***
				(5.90)	(4.77)	(5.10)
$TURN$				-0.1789***	-0.0286	-0.0300
				(-4.58)	(-0.76)	(-0.80)
$ILLIQ$				-0.0128**	0.0004	0.0111*
				(-2.52)	(0.08)	(1.89)
β				0.6508***	0.7786***	0.8364***
				(3.40)	(4.00)	(4.24)
MAX					-0.1144***	-0.0730***
					(-16.04)	(-7.17)
$IVOL$						-0.1874***
						(-5.42)
Constant	0.5751**	0.5711**	0.5867**	1.2494***	1.6658***	1.9087***
	(2.43)	(2.43)	(2.50)	(4.46)	(5.82)	(6.64)
R^2	0.008	0.009	0.011	0.088	0.091	0.093

Table 25: Fama-MacBeth Return Regressions on IS_φ and DUM_CGO

The table reports the slopes and their t-values of Fama-MacBeth regressions,

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}DUM\_CGO_{i,t} + \lambda_{3,t}IS_{\varphi i,t} + \lambda_{4,t}DUM\_CGO_{i,t} \times IS_{\varphi i,t} + \Lambda_t X_{i,t} + \epsilon_{i,t+1},$$

where $X_{i,t}$ is a vector of other firm characteristics. The regressions are run for monthly data from January 1962 to December 2013. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
DUM_CGO	0.3216***	0.3180***	0.3078***	0.2265***	0.1938***	0.1712***
	(3.72)	(3.72)	(3.58)	(4.79)	(4.11)	(3.72)
IS_φ			-1.2217***	-1.4688***	-1.3625***	-1.3430***
			(-3.11)	(-4.89)	(-4.55)	(-4.32)
$DUM\_CGO \times IS_\varphi$		-0.5899	0.6318	0.6642	0.7194	0.8236*
		(-1.39)	(1.29)	(1.37)	(1.48)	(1.65)
$ISKEW$				-0.1012***	-0.0163	-0.0236
				(-5.71)	(-0.96)	(-1.36)
$SIZE$				-0.1533***	-0.1941***	-0.2163***
				(-4.11)	(-5.14)	(-5.71)
BM				0.3170***	0.2703***	0.2645***
				(6.19)	(5.28)	(5.13)
MOM				0.0086***	0.0070***	0.0076***
				(5.87)	(4.74)	(5.06)
$TURN$				-0.1825***	-0.0261	-0.0252
				(-4.66)	(-0.69)	(-0.67)
$ILLIQ$				-0.0129**	0.0008	0.0116*
				(-2.49)	(0.15)	(1.96)
β				0.6529***	0.7921***	0.8476***
				(3.41)	(4.06)	(4.30)
MAX					-0.1204***	-0.0788***
					(-16.79)	(-7.74)
$IVOL$						-0.1883***
						(-5.40)
Constant	0.5751**	0.5713**	0.5816**	1.2498***	1.6964***	1.9352***
	(2.43)	(2.43)	(2.48)	(4.46)	(5.93)	(6.75)
R^2	0.008	0.010	0.011	0.088	0.091	0.094

Table 26: Portfolio Sorted by CGO and Asymmetry Measures

The table reports the average returns and their t-values for quintile portfolios sorted by CGO and then by $ISKEW$, IE_{φ} or IS_{φ} based on monthly data from January 1962 to December 2013. CGO1 and CGO5 denote the lowest and highest quintiles for CGO, and $P1$ and P_5 denote the lowest and highest quintiles for $ISKEW$, IE_{φ} and IS_{φ}, respectively. Significance at 1% and 5% levels are indicated by *** and **, respectively.

	$ISKEW$			IE_{φ}			IS_{φ}		
Proxy	P1	P5	P5-P1	P1	P5	P5-P1	P1	P5	P5-P1
CGO1	0.751***	0.286	-0.465***	0.644***	0.454*	-0.190**	0.635**	0.404	-0.231***
t-stat	(2.93)	(1.09)	(-4.22)	(2.70)	(1.76)	(2.10)	(2.57)	(1.57)	(-2.75)
CGO2	0.572***	0.429*	-0.143	0.643***	0.440*	-0.202***	0.666***	0.456*	-0.210***
t-stat	(2.66)	(1.79)	(-1.48)	(2.96)	(1.92)	(-2.81)	(2.98)	(1.94)	(-3.11)
CGO3	0.522***	0.601***	0.078	0.683***	0.594***	-0.089	0.737***	0.624***	-0.113*
t-stat	(2.78)	(2.69)	(0.81)	(3.51)	(2.78)	(-1.28)	(3.60)	(2.82)	(-1.67)
CGO4	0.662***	0.771***	0.110	0.816***	0.675***	-0.141**	0.824***	0.775***	-0.049
t-stat	(3.62)	(3.66)	(1.22)	(4.42)	(3.26)	(-2.00)	(4.19)	(3.65)	(-0.76)
CGO5	0.937***	1.104***	0.167*	1.212***	1.164***	-0.047	1.236***	1.169***	-0.067
t-stat	(4.94)	(5.30)	(1.79)	(6.23)	(5.42)	(-0.65)	(6.02)	(5.19)	(-0.91)
Avg(C1-C5)	0.689***	0.638***	-0.051	0.799***	0.666***	-0.134***	0.820***	0.685***	-0.134***
t-stat	(3.50)	(2.90)	(-0.69)	(4.06)	(3.10)	(-2.84)	(3.97)	(3.11)	(-3.32)