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 measure, skewness, ours are based on the tail distribution 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, consistent with theoretical models such as 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

In theory, Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2008) and Han and Hirshleifer (2015) show that greater upside asymmetry is associated with lower expected return. Empirically, using skewness, the most popular measure of asymmetry, Harvey and Siddique (2000), Zhang (2005), Smith (2007), Boyer et al. (2010), and Kumar (2009) find empirical evidence supporting the theory. However, Bali et al. (2011) find that skewness is not statistically significant in explaining the expected returns in a more general set-up.[1] More recently, An et al. (2015) find that the correlation between skewness and expected return depends on capital gains overhang (CGO). In short, the evidence on the ability of skewness in capturing asymmetry to explain the cross-section stock returns is mixed and inconclusive.

In this paper, we propose two distribution-based measures of asymmetry. We argue that skewness, as a measure of asymmetry, is limited because two distributions can have the same skewness while quite different in asymmetry. Intuitively, asymmetry reflects a characteristic of the entire distribution, but skewness consists of only the third moment. Therefore, even if the skewness is inconclusive in explain asset returns, it does not mean asymmetry matters any less.[2] This clearly comes down to how we can measures asymmetry adequately. Our first measure of asymmetry is a simple difference between the upside probability and downside probability, which captures the degree of upside asymmetry based

[1]The results are similar for applying the realized or regression estimated expected idiosyncratic skewness. For brevity, we do not present results for expected idiosyncratic skewness, but they are available upon request.

[2]Previous literature also realizes the limitation of skewness and try to measure lottery-type stocks using information beyond skewness. Kumar (2009) proposes using the combination of stock price, idiosyncratic volatility and idiosyncratic skewness.

on probabilities. The second measure is a modified entropy measure, modified from Racine and Maasoumi (2007), that assesses asymmetry based on integrated density difference. Statistically, we show via simulations that our distribution-based measures can capture asymmetry more accurately than skewness, the third moment only measure.

Empirically, we examine the explanatory power of both skewness and our new measures in the cross-section of stock returns, and find that our measures explain well the returns and skewness does not. We conduct our analysis with two approaches. In the first approach, we study their performances in explaining the returns using Fama and MacBeth (1973) regressions. Using data from January 1962 to December 2013, we find that there is no apparent relation between the skewness and the cross-sectional average returns, which is consistent with the findings by 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 tail 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 or to our new asymmetry measures. We find that while high skewness portfolios do not necessarily imply low returns, high upside asymmetries based on the new measures do associate with low returns.

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), though focusing on skewness, in fact show that tail asymmetry matters for the expected returns. 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 winner picks instead of loser stocks), that investors favor the adoption of investment products or strategies that produce a higher probability of large gains as opposed to large losses.

Consistent with these studies, our measures reflect investor's preference of lottery-type assets or strategies. Moreover, they also reflect the degree of short sale constraints on stocks. The more difficult the short sell, the more the distribution of the stock return is likely to lean towards the upper tail, and the lower the return expected due to the likely over-pricing of the stock (see Acharya et al. (2011), and Jones and Lamont (2002)). This is also related to strategic timing of information by firm managers (Acharya et al. (2011)).

In this paper, we also examine the relation between asymmetry and return conditional on sentiment and CGO, respectively. We find that skewness is only negatively significant related to the stock expected return during high sentiment period (when sentiment is above the 0.5 or 1 standard deviation of the sentiment time series) or for firms whose representative investors experienced capital losses. The results are robust to alternative skewness measures: the total skewness, the idiosyncratic skewness and their expected counterparts.[3] In contrast, using our measures, the expected returns are unconditionally negative for lottery-type stocks. The results are consistent with the theory that preference for upside asymmetry can be induced from the over-weighting of very low probability events (Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2008)). For sentiment, Baker and Wurgler (2006) point out firms which are difficult to arbitrage should be more overvalued during high sentiment periods. Our empirical documents indicate that high skewness firms can still face high arbitrage risk, which are difficult to arbitrage, then the evaluation of them are largely impacted by sentiment. However, high upside asymmetry stock does not necessary associate with arbitrage risk, it should be less influenced by sentiment. Our conditional result on sentiment is consistent with Baker and Wurgler (2006)'s theory. Stambaugh et al. (2012, 2015) consider impediments to short selling as the major obstacle to eliminating sentiment-driven mispricing. To the extent such mispric-

[3]The total skewness and expected idiosyncratic skewness results are available from the authors upon request.

ing exists, overpricing should then be more prevalent than underpricing, and overpricing should be more prevalent when market-wide sentiment is high. For CGO, Wang et al. (2014) find that among stocks where average investors face prior losses, there could be a negative risk-return relation. And recently, An et al. (2015) document that the skewness preference only holds for capital loss stocks. As we mentioned before, high skewness stocks can still associate with high arbitrage risk, thus its negative relationship with expected return exist among stocks with capital loss which consistent with by Wang et al. (2014)'s argument. But high upside asymmetry stock does not necessary associate with high risk, thus its relationship with expected return is less affect by CGO level.

The paper is organized as follows. Section 2 presents our new asymmetry measures. Section 3 provides the measures as asymmetry tests for simulated data and size portfolios. Section 4 provides the empirical results. Section 5 concludes.

2 Asymmetry Measures

In this section, we introduce our two asymmetry measures and also discuss their estimation in practice.

Let x be the daily excess return of a stock for total asymmetry or the residual after adjusted statistical benchmark from risk factors for idiosyncratic asymmetry. Without loss of generality, x is standardized with mean 0 and variance 1. To assess the upside asymmetry of a stock return distribution, we consider its excess tail probability (ETP), which 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.[4] The first term measures the cumulative chance of gains, while the second measures the chance cumulative 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 high upside potentials and dislike stocks with high possibility of big loss (Kelly and Jiang (2014), Barberis and Huang (2008), Kumar (2009), Bali et al. (2011) and Han and Hirshleifer (2015)). This implies that, every thing else equal, the asset expected return will be lower than otherwise.

Our second measure of distributional asymmetry is a 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

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

almost surely. Then any difference between $f(x)$ and $f(\tilde{x})$ is clearly a measure of asymmetry. Shannon (1948) first introduced entropy measure, and Kullback and Leibler (1951) makes 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

[4]Since a certain number of sample size is needed for density estimation, we focus on using 1 standard deviation only, but the results are qualitatively similar with 1.5 standard deviations and other convectional levels.

normalization of the Bhattacharya-Matusita-Hellinger measure,

$$S_\rho = \frac{1}{2}\int_{-\infty}^{\infty}(f_1^{\frac{1}{2}} - f_2^{\frac{1}{2}})^2 dx,^5 \tag{3}$$

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 in between 0 and 1; (3) it is a metric, implying that a larger number S_ρ indicates greater distance, and the measure is comparable; (4) it is invariant under continuous and strictly increasing transformation on the underlying variables.

Assume that the density is smooth enough. Then we have the following interesting relation (see Appendix A.1 for the proof) between S_ρ and various moments,[6] such as 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_i's are constants and $o(\sigma^4)$ denotes the higher than 4th order terms. It is clear that S_ρ is related to the skewness. Every thing else equal, higher skewness means greater S_ρ and greater asymmetry.[7] However, in practice for stocks, it is impossible to control for all other moments, and hence a high skewness will not necessarily imply a high S_ρ.

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

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[5] $S_\rho = \frac{1}{2}\int \left[1 - \frac{f_2^{\frac{1}{2}}}{f_1^{\frac{1}{2}}}\right]^2 dF_1(x) = \frac{1}{2}\int \left[1 - \frac{f(-x+2\mu_x)^{\frac{1}{2}}}{f(x)^{\frac{1}{2}}}\right]^2 dF_(x)$

[6] From footnote 5, S_ρ has the expectation form, then it can be written as the linear combination of moments. In contrast, E_φ does not has the expectation form, thus it can not be decomposed into moments.

[7] Our measure is also consistent with the intuition in Kumar (2009). He indicates that cheap and volatile stocks with high skewness attract investors who also tend to invest in state lotteries. But our measure is more adequate and simple.

the upside asymmetry. Hence, we modify S_ρ by defining our second measure of asymmetry as

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

The sign of E_φ ensures that S_φ has the same sign as E_φ, so that the magnitude of S_φ indicates upside potential. In fact, S_φ is closely related to E_φ. 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 information of the distribution. However, empirically, their performances can clearly vary from one application to another.

The econometric estimation of E_φ is trivial as one can simply replaces 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 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 weakly time dependent assumption, which is reasonable assumptions for stock returns, the estimated density converges to the actual density (see, e.g., Li and Racine (2007) for details). With the above, we can estimate $\hat{S}_\varphi$ by computing the associated integrals numerically.

3 Asymmetry Tests

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

Many commonly used skewness tests, such as D'Agostino (1970), assume normality under the null hypothesis. Therefore, they are mainly tests of normality and they could reject the null when the data is symmetric but not normally distributed. Since we are interested in testing for return asymmetry rather than normality, it is inappropriate to apply those tests in our setting directly. The skewness test we employ is based on bootstrap resampling method. As suggested by Horowitz (2001), bootstrap with pivotal test statistics can achieve asymptotic refinement. So we develop the skewness test using pivotized (studentized) skewness as the test statistic. Monte Carlo simulations show that this test has correct size and good finite sample powers. The entropy tests of asymmetry mainly follow the test proposed by Racine and Maasoumi (2007) and Maasoumi and Racine (2008) with a slight variation. We use the studentized S_ρ which has, in simulations, better finite sample properties than the original entropy test proposed in Racine and Maasoumi (2007). In this way, the entropy test and the skewness test share the same setup and the only difference is how the test statistic is computed. Due to the heavy computational demands, following Racine and Maasoumi (2007) and Maasoumi and Racine (2008), significance levels are obtained via stationary block bootstrap with 399 replications.

Consider first the case in which skewness is a good measure. We simulate the data, with $n = 500$, independently from two distributions: $N(120, 240)$ and $\chi^2(10)$. The first is a normal distribution with mean 120 and variance 140, and the second is a chi-squared distribution with 10 degrees of freedom. With $M = 1000$ 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. There are no rejections for the normal data, and there are always rejections for the chi-squared. Hence, all the measures work well in this simple case.

[Insert Table 1 about here]

Consider now a more complex situation. The difference is defined as the difference of two beta distribution Beta(1,3.7)-Beta(1.3,2.3). As plotted in Figure 1, it has longer left tail and negative asymmetry.[8] 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-statistics of 0.13. In contrast, both S_φ and E_φ have highly significant negative values which correctly captures the asymmetric feature of Beta(1,3.7)-Beta(1.3,2.3).

[Insert Figure 1 about here]

[8] The difference of two beta distribution is a well-defined distribution whose density function is provided by Pham-Gia et al. (1993) and Gupta and Nadarajah (2004).

To understand the testing results, Figure 2 plots the distributions of two beta distributions, Beta(1,3.70) and Beta(2,12.42), which have roughly the same skewness value of 1. It is clear that Beta(1,3.70) has longer right tail and and higher upside asymmetry. This can by captured by both S_φ and E_φ, but not skewness.

[Insert Figure 2 about here]

The second example compares the performance of the distribution based asymmetry measure S_ρ and skewness, when they are used to statistically test asymmetry in commonly used size portfolios. The test portfolios we use are value-weighted and equal-weighted monthly returns of decile stocks portfolios sorted by market capitalization. The sample period is from January 1962 to December 2013 (624 observations in total). In general, we find that entropy can detect asymmetry more effectively than skewness in both empirical applications and in simulations.

Table 2 reports the results for $SKEW$ and S_ρ tests (the results of using E_φ are omitted for brevity). For the value-weighted size portfolios, the entropy test rejects symmetry for the first 3 smallest and the 5th size portfolios at the convectional 5% level. In contrast, skewness test can only detect asymmetry for the smallest size portfolio. For the equal-weighted size portfolios, the 1st, 2nd, 7th, and the 10th are asymmetric based on the entropy test at the same significance level. In contrast, only the 1st, and the 7th have significant asymmetry according to skewness test. Overall, tests based on the entropy measures generally detect more asymmetry than skewness test.

[Insert Table 2 about here]

4 Empirical Results

4.1 Data

We use data from Center for Research in Securities Prices (CRSP), 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 \$5 and \$1,000. In order to mitigate the concern of double-counted stock trading volume in NASDAQ, we, following Gao and Ritter (2010), adjust the trading volume to calculate turnover ratio ($TURN$) and Amihud (2002) ratio ($ILLIQ$). The latter is normalized to account for inflation and is truncated at 30 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 it is annually updated.

Following Bali et al. (2011), we compute volatility (VOL) and maximum (MAX) of stock returns as the standard deviation and the maximum return of daily returns of the previous month. In addition, we compute idiosyncratic volatility ($IVOL$) of a stock as the standard deviation of daily idiosyncratic returns of the month. We calculate skewness ($SKEW$), idiosyncratic skewness ($ISKEW$), and proposed asymmetry measures (E_φ and S_φ) and idiosyncratic counterparts (IE_φ and IS_φ) using return and benchmark adjusted residuals. We calculate proposed asymmetry using the daily information up to 12 months in order to have accurate measures. We use last month excess returns or risk adjusted-returns (the excess returns which adjusted for Fama-French three factors, see Brennan et al. (1998)) as the proxy for short-term reversals (REV or $REVA$ for risk adjusted-returns).

Table 3 summarizes the correlation of volatility and the asymmetry measures. For comparison, the table reports the results for both the total measures (based on the raw returns) and the idiosyncratic measures (based on the market model residuals). It is interesting that the correlations in the similar magnitude in either case. $ISKEW$ has very small correlations with IE_{φ} or IS_{φ}. It indicates the importance to use our proposed asymmetry measures rather than skewness as proxy. And IE_{φ} or IS_{φ} have a high correlation of over 67%. The volatility has around 8% correlation with the skewness, and much lower correlation with IE_{φ} or IS_{φ}. The simple correlation analysis shows that the new measure capture information beyond volatility and skewness.

[Insert Table 3 about here]

Two sentiment proxies by Baker and Wurgler (2006, 2007), and Huang et al. (2015) are applied in our paper. 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.[9] Following Grinblatt and Han (2005), we calculate the capital gain overhang (CGO) for representative investors for each month using weekly price and turnover ratio. The reference price is weighted average of past prices at which investor purchase stocks but never sell. As in Grinblatt and Han (2005), we use information for 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 price at week $t-1$ and reference price at week t (divided by the price at week $t-1$). In this way, the complicated microstructure effect can be avoided. The details of all the variables are

[9] 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/.

defined in Appendix A.2.

4.2 Firm Characteristics and Asymmetries

In this subsection, we examine what types of stock are associated with asymmetries as measures 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 0.5 percentile and 99.5 percentile. The Fama-MacBeth standard errors are adjusted using the Newey and West (1987) correction with three lags.[10]

Table 4 provides the results. Consistent with other studies such as Boyer et al. (2010) and Bali et al. (2011), $ISKEW$ is negatively related to $SIZE$ and BM, positively related to MOM, $ILLIQ$, and market beta (β), but is insignificant 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 asymmetry of firms. As a result, different measures show similar relations to them.

However, 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, then it is not surprising

[10]The results here and later are qualitatively similar if we use up to 24 lags.

that they are related to turnover ratios positively and significantly.

[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 compare them with skewness, the previously commonly used proxy for asymmetry.

One of the fundamental problems in finance is to understand which factor loadings or characteristics can explain the cross section of stock returns. To compare the 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 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, the regression slopes are -3.4598 and -0.8584 (the third and the fourth columns). Both of 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 (the second column, the univariate regression), and statistically insignificant. Hence, it is inconclusive on the ability of skewness to explain cross section of stock returns over period from January 1962 to December 2013.[11]

[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 little 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 benchmark 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 RA_i. Then we 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, though 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 before. The results reaffirm that new asymmetry have significant power in explaining the cross-section of stock returns, while skewness measure barely matters.[12]

[11]Instead of using the realized skewness $ISKEW$, one can use the estimated future skewness as Boyer et al. (2010) or Bali et al. (2011), the results are still insignificant. They are available upon request

[12]If we further remove the tail risk factor proposed by Kelly and Jiang (2014), our results from risk-adjusted returns are qualitatively similar.

[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 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, 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 does not show any monotonic pattern. The return difference is 0.073% per month, which is not economically significant nor statistically significant. Hence, stock with high skewness do not necessarily imply low return, indicating that skewness is not adequate, since theoretical models such as Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2008) and Han and Hirshleifer (2015), generally imply high asymmetry leads to lower return or show that greater upside asymmetry is associated with lower expected return.

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 reports 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 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 show clearly an approximate pattern of deceasing returns across the deciles. Moreover, the spread portfolio has a (negatively) large value of -0.179% per month that 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 too. Overall, the results show strongly that high $IE_{\varphi,i,t}$ leads to low return, and it 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. This is not surprising as both measures are similar and their time-series average of cross-sectional correlation is around 68%. In summary, the empirical results support that both $IE_{\varphi,i,t}$ and $IS_{\varphi,i,t}$, improving upon skewness, are useful measures of asymmetry, and they explain the cross-section of stocks returns in a way consistent with theory.

[Insert Table 8 about here]

[Insert Table 9 about here]

4.5 Asymmetry and Sentiment

In this subsection, we examine how asymmetry measures vary during high and low sentiment periods. Stambaugh et al. (2012, 2015) find that anomalous returns are high following high sentiment periods because mispricing is likely more prevalent when the investor sentiment is high. Since asymmetry measures are related to lottery type of 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 as those months when the Baker and Wurgler (2006) sentiment index (BW index henceforth) is one standard deviation above its mean. The second is low sentiment periods, when the BW index is one standard deviation below its mean.[13]

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. We run the regressions in high and low sentiment periods separately.

Table 10 reports the results. Columns 2–5 show that, conditional on high sentiment, skewness always has negative effect on expected return no matter there are various controls or none. However, when the sentiment is low, their loadings, provided in Columns 6–9, are always positive. [14] The results seem to shed light on the earlier mixed evidence on the ability of skewness to explain the returns.[15]

[Insert Table 10 about here]

Consider now the Fama-MacBeth regressions of the excess returns on IE_φ conditional on high and low sentiment periods. Table 11 shows that IE_φ always have negatively loadings, though it is more significant in high sentiment periods. The same pattern is observed on IS_φ in Table 12. Overall, the results show that skewness is quite sensitive to

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

[14]The result we shown is conditional on the previous month sentiment, and the result is similar for the current month sentiment.

[15]Boyer et al. (2010) show that the expected idiosyncratic skewness has a significant negative effect on the expected return, while Bali et al. (2011) point out the effect is significant positive applying several skewness measures: the total skewness, the idiosyncratic skewness and the expected total skewness (In the full specifications, these average coefficients on the skewness variables become statistically insignificant, but still positive according to Bali et al. (2011)). Boyer et al. (2010)'s estimation period is from December 1987 to November 2005, which is shorter compared with the period from July 1962 to December 2005 in Bali et al. (2011).

sentiment, while IE_φ and IS_φ are much less so.[16]

[Insert Table 11 about here]

[Insert Table 12 about here]

4.6 Asymmetry and Capital Gains Overhang

In this subsection, we examine how the effect of asymmetry on stock return 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 the similar way to skewness which only capture 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 the past turnover. Then 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 if we use more accurate measure of asymmetry.

As in An et al. (2015), we add CGO and its interaction with $ISKEW$ to the early Fama-MacBeth regressions of the excess returns on $ISKEW$,

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

[16]Using risk adjusted return, we find the effects of IE_φ and IS_φ are even stronger in low sentiment periods than what observed using excess return, while the effect of skewness is similar. The results are available upon request.

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

Table 13 reports the results. With any controls of other firm characteristics, the third column of the table shows that, the effect of skewness on stock return changes with CGO in the absence of any controls. The rest of the columns provide similar results, consistent with An et al. (2015)'s finding that the skewness preference depends on the CGO level: investors like positive skewed stocks only when they experienced a capital loss.

[Insert Table 13 about here]

Replacing $ISKEW$ by either IE_φ or IS_φ, Table 14 and 15 report the results of the same regressions. IE_φ or IS_φ always matters regardless of the level of CGO. Moreover, in all cases, there are no strong interaction effects between our new measures and CGO at 5 % level. Hence, using our new asymmetry measures, the preference of positive asymmetric stocks is invariant with respect to CGO.

[Insert Table 14 about here]

[Insert Table 15 about here]

To examine the effect of CGO further, 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, and then, within each CGO portfolio, we sort stocks into quintile portfolios by one of asymmetry measures: $ISKEW$ or IS_φ or IE_φ. Table 16 reports the equal-valued excess returns of some selected portfolios for brevity. Only in the lowest quintile of CGO, the return on the spread portfolio of $P5-P1$ (the difference between the highest and lowest skewness stocks), -0.465%, is significant, reaffirming that skewness is tied to CGO level. In contrast, the spread portfolios for IS_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 is fairly robust.

[Insert Table 16 about here]

5 Conclusion

In this paper, we propose two distribution-based measures of stock return asymmetry to substitute skewness in asset pricing tests. They are mathematical more accurate than skewness. The first one is based on the probability difference of upside potential and downside loss of a stock, and the second is based on entropy which is 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 firm-level, but also in the cross section of portfolios sorted based on the new asymmetry measures. In contrast, the empirical results from skewness is elusive. Our empirical results are consistent with the predictions of theoretical models such as Barberis and Huang (2008) and Han and Hirshleifer (2015).

Appendix

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

A.1 Proof of Equation (4)

Following Maasoumi and Theil (1979)'s, 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 $g(x) = \frac{f(-x+2\mu)}{f(x)}$, then we 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 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, applying the Taylor expansion of $g(x)^{\frac{1}{2}}$ at the mean μ, we obtain

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

then, take the expectation, we obtain

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

Hence, (14) becomes

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

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

A.2 Variable Definitions

- E_φ: Excess tail probability or total excess tail probability of stock i (at one standard deviation) in month t is defined as (1), 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), 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: Idiosyncratic E_φ of stock i (at one standard deviation) in month t is defined as (1), x is the standardized residual after adjusted market factor. 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:

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

  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: Idiosyncratic S_φ of stock i (at one standard deviation) in month t is defined as (5), x is the standardized residual after adjusted market factor. 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 $t-1$:

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

- 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. Then $IVOL$ of stock i in month t is 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 $t-12$, the same with 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 the year, and σ_i is the standard deviation of returns of stock i in the year.
- IDIOSYNCRATIC SKEWNESS ($ISKEW$): Idiosyncratic skewness of stock i in month t is computed using daily residuals $\epsilon_{i,d}$ (20) instead of 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 in month t 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 latest fiscal year ending in the prior calendar year. Our measure of book-to-market ratio, BM, is defined as the natural log of the book-to-market ratio.
- 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 6 months, with the previous one 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 ($REVA$): It is defined as the adjusted-return (the excess return which adjusted for Fama-French three factors (Brennan et al. (1998))) over the previous month.
- TURNOVER ($TURN$): $TURN$ is calculated monthly as the adjusted monthly trad-

ing volume divided by shares outstanding.

- ILLIQUIDITY ($ILLIQ$): Following Amihud (2002), the proxy for daily stock illiquidity is from normalizing $L_{i,d} = |R_{i,d}|/dv_{i,t}$. It is the ratio of absolute change of price $r_{i,d}$ to the dollar trading volume $dv_{i,d}$ for stock i at day d. The monthly $ILLIQ$ is the daily average of the illiquidity ratio for each stock. To get an accurate estimate of monthly Amihud ratio, we drop the months for stocks if the number of the monthly observations is less than 15. Following Acharya and Pedersen (2005), we also normalized the Amihud ratio to adjust for inflation and truncated it at 30 to eliminate the effect of outliers (the stocks with transaction cost larger than 30% of the price),

$$ILLIQ_{i,t} = \min(0.25 + 0.3L_{i,t} \times \frac{\text{capitalization of market portfolio}_{\text{t}-1}}{\text{capitalization of market portfolio}_{\text{July 1962}}}, 30). \quad (27)$$

- CAPITAL GAINS OVERHANG (CGO): Following Equation (9), page 319, and Equation (11), page 320 in Grinblatt and Han (2005), the capital gains overhang (CGO) at week w is defined as:

$$CGO_w = \frac{P_{w-1} - RP_w}{P_{w-1}}, \quad (28)$$

where P_w is the stock price at the end of week w, and RP_w is the reference price for each individual stock which defined as follows.

$$RP_w = k^{-1} \sum_{n=1}^{W} (V_{w-n} \prod_{\tau=1}^{n-1} (1 - V_{w-n+\tau})) P_{w-n}, \quad (29)$$

where V_w is the turnover in week w. W is 260, the number of weeks in the previous five years. k is the constant that makes the weights on past prices sum to one. Weekly turnover is calculated as the weekly trading volume divided by the number of shares outstanding. The weight on P_{w-n} reflects the probability that share purchased at week $w-n$ has not been traded since. The market price is lagged by one week, and the monthly CGO is just the last week CGO within each month. The CGO variable ranges from 1962 to 2013.

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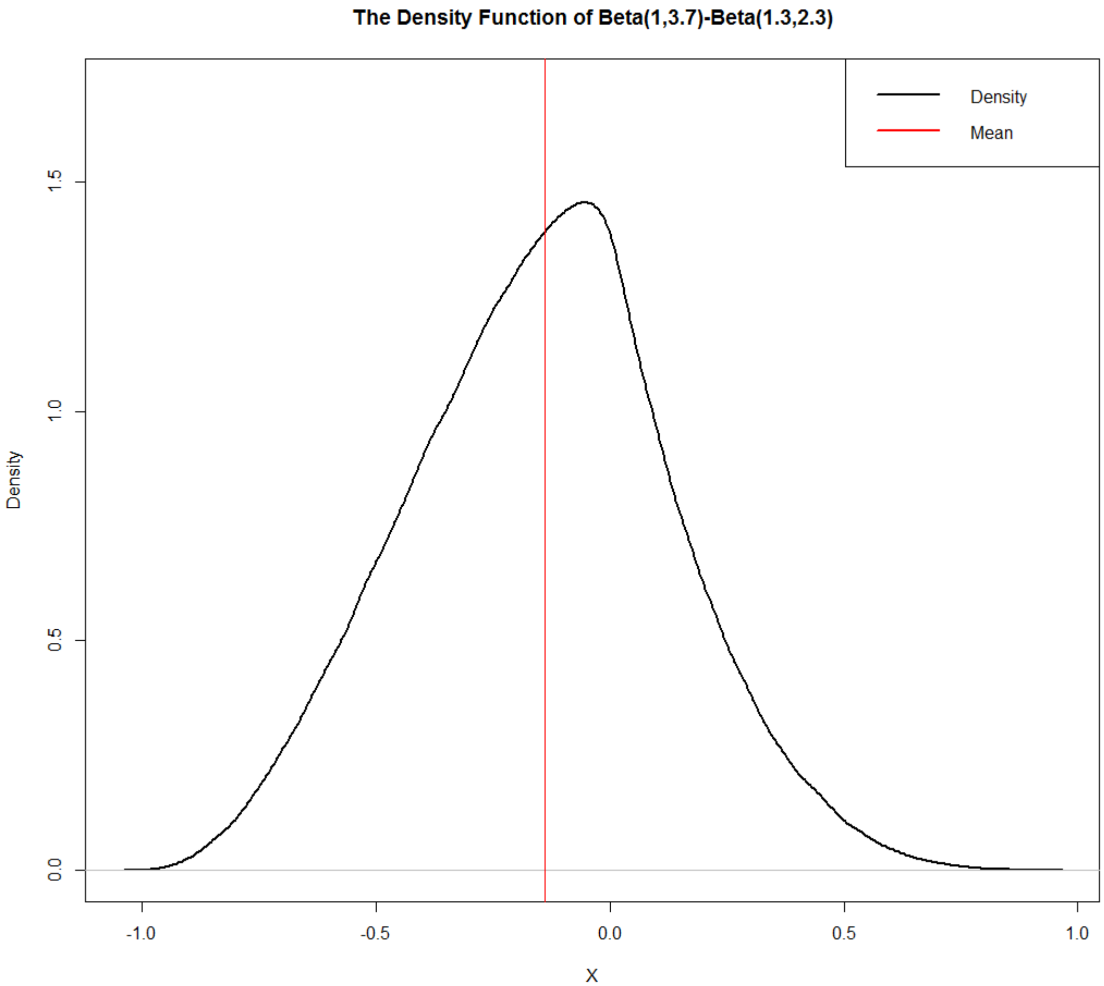

Figure 1: Asymmetric, skewness=0

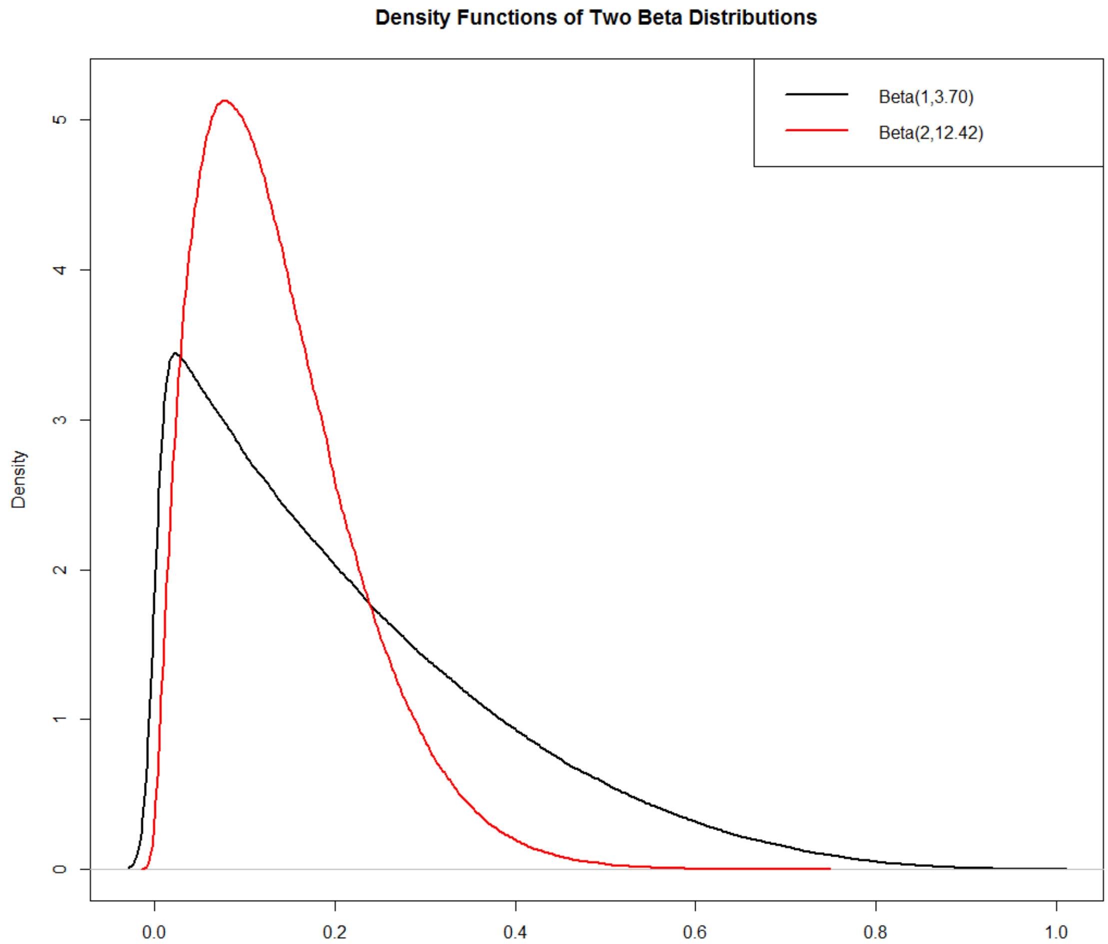

Figure 2: Different Asymmetry, skewness=1

Table 1: Simulation

The table provides the average values and associated t-statistics (in parentheses) of skewness($SKEW$), E_φ, and S_φ from 1,000 draws simulated from a normal distribution, a chi-squared distribution of degree 10 and a Beta difference distribution. 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: Testing Asymmetry for Size Portfolios

The table reports the skewness and entropy tests of asymmetry 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 Asymmetry Measures and Volatility

Panel A provides the time series average of the correlations of 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 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 characteristics variables (in the first column) for monthly data from January 1962 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 11: 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 characteristics variables (in the first column) for monthly data from January 1962 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 12: 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 characteristics variables (in the first column) for monthly data from January 1962 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 13: Fama-MacBeth Return Regressions on $ISKEW$ and CGO

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

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

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% and 5% levels are indicated by *** and **, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
CGO	0.6089***	0.5384***	0.5507***	0.3382***	0.2476***	0.4203***
	(5.14)	(4.35)	(4.49)	(4.24)	(3.12)	(5.80)
$ISKEW$			0.0172	-0.0729***	0.0103	0.0044
			(0.63)	(-4.15)	(0.61)	(0.25)
$CGO \times ISKEW$		0.1686***	0.1253***	0.1465***	0.1750***	0.2003***
		(3.95)	(3.06)	(3.95)	(4.72)	(5.24)
$SIZE$				-0.1466***	-0.1843***	-0.1989***
				(-3.96)	(-4.91)	(-5.21)
BM				0.3156***	0.2673***	0.2188***
				(6.13)	(5.20)	(4.14)
MOM				0.0084***	0.0071***	0.0056***
				(6.04)	(5.10)	(3.61)
$TURN$				-0.1923***	-0.0389	-0.0099
				(-4.98)	(-1.05)	(-0.27)
$ILLIQ$				-0.0122**	0.0009	0.0153**
				(-2.41)	(0.17)	(2.53)
β				0.6459***	0.7710***	0.7627***
				(3.40)	(3.98)	(3.78)
MAX					-0.1163***	0.0237***
					(-16.36)	(2.71)
$IVOL$						-0.3895***
						(-12.58)
REV						-0.0457***
						(-12.64)
Constant	0.7628***	0.7456***	0.7378***	1.3244***	1.7255***	1.9378***
	(3.58)	(3.52)	(3.55)	(4.85)	(6.18)	(6.73)
R^2	0.012	0.014	0.016	0.088	0.091	0.099

Table 14: Fama-MacBeth Return Regressions on IE_φ and CGO

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

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

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% and 5% levels are indicated by *** and **, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
CGO	0.6089***	0.5833***	0.5821***	0.3764***	0.3007***	0.4848***
	(5.14)	(4.83)	(4.86)	(4.83)	(3.86)	(6.80)
IE_φ			-3.5006***	-5.2158***	-4.4470***	-3.4496***
			(-2.80)	(-6.51)	(-5.57)	(-4.14)
$CGO \times IE_\varphi$		2.1762	2.7282	2.0938	2.2846	3.8479
		(0.80)	(1.02)	(0.83)	(0.91)	(1.45)
$ISKEW$				-0.1050***	-0.0202	-0.0257
				(-6.16)	(-1.23)	(-1.48)
$SIZE$				-0.1514***	-0.1886***	-0.2018***
				(-4.09)	(-5.02)	(-5.28)
BM				0.3116***	0.2645***	0.2169***
				(6.08)	(5.17)	(4.11)
MOM				0.0086***	0.0073***	0.0057***
				(6.25)	(5.28)	(3.72)
$TURN$				-0.1821***	-0.0308	-0.0022
				(-4.70)	(-0.83)	(-0.06)
$ILLIQ$				-0.0124**	0.0005	0.0146**
				(-2.45)	(0.10)	(2.44)
β				0.6496***	0.7723***	0.7606***
				(3.41)	(3.98)	(3.77)
MAX					-0.1151***	0.0232***
					(-16.13)	(2.65)
$IVOL$						-0.3814***
						(-12.30)
REV						-0.0458***
						(-12.65)
Constant	0.7628***	0.7496***	0.7601***	1.3661***	1.7626***	1.9631***
	(3.58)	(3.54)	(3.60)	(4.99)	(6.30)	(6.81)
R^2	0.012	0.013	0.015	0.089	0.092	0.099

Table 15: Fama-MacBeth Return Regressions on IS_φ and CGO

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

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

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)
CGO	0.6089***	0.5846***	0.5851***	0.3789***	0.2971***	0.4838***
	(5.14)	(4.79)	(4.81)	(4.79)	(3.76)	(6.76)
IS_φ			-0.6785**	-1.0500***	-0.9275***	-0.7233***
			(-2.12)	(-4.70)	(-4.11)	(-3.00)
$CGO \times IS_\varphi$		0.9412	1.3068	0.9106	1.0056	1.4104*
		(1.21)	(1.63)	(1.18)	(1.31)	(1.79)
$ISKEW$				-0.0996***	-0.0134	-0.0205
				(-5.63)	(-0.79)	(-1.15)
$SIZE$				-0.1514***	-0.1919***	-0.2042***
				(-4.09)	(-5.11)	(-5.36)
BM				0.3160***	0.2658***	0.2178***
				(6.15)	(5.18)	(4.12)
MOM				0.0087***	0.0074***	0.0057***
				(6.21)	(5.25)	(3.73)
$TURN$				-0.1862***	-0.0283	0.0009
				(-4.79)	(-0.75)	(0.02)
$ILLIQ$				-0.0125**	0.0010	0.0149**
				(-2.43)	(0.18)	(2.47)
β				0.6495***	0.7837***	0.7677***
				(3.40)	(4.04)	(3.81)
MAX					-0.1214***	0.0186**
					(-16.90)	(2.12)
$IVOL$						-0.3836***
						(-12.33)
REV						-0.0455***
						(-12.58)
Constant	0.7628***	0.7501***	0.7563***	1.3678***	1.7947***	1.9874***
	(3.58)	(3.54)	(3.58)	(4.99)	(6.40)	(6.91)
R^2	0.012	0.013	0.015	0.089	0.092	0.099

Table 16: 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)