Is Stock Return Predictability of Option-implied Skewness Affected by the Market State?

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ABSTRACT

We use Bakshi, Kapadia, and Madan (2003) methodology to measure option-implied *ex ante* skewness of the underlying stocks' risk-neutral returns distribution. We find that the subsequent month return of a low skewness quintile exceeds a high skewness quintile by approximately 1% per month. Furthermore, the coefficients on skewness in Fama-MacBeth cross-sectional regressions are negative and statistically significant even after controlling for firm-characteristic variables that are known to forecast stock returns. Specifically, the cross-sectional stock return predictability of skewness is only significant during periods of low market return and high investor sentiment. In addition, we find that predictive power of skewness is mainly caused by market state rather than sentiment. Our findings suggest that investors consider high option-implied skewness stocks as lottery-like stocks.

Keywords: Option-implied skewness, Cross-sectional return predictability, Skewness preference

JEL classification: G11, G12, G14

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1. Introduction

A long history of finance literature has investigated whether investors consider return skewness when they invest. Arditti (1967) and Scott and Horvath (1980) show that under general assumptions, investors prefer a positive skewness of returns distribution. Although skewness is largely affected by the outliers of returns, measuring skewness is an important task. Researchers have examined several methodologies to compute skewness; including co-skewness, idiosyncratic skewness and *ex ante* version of skewness.[1]

The recent literature has attempted to measure *ex ante* skewness to investigate the pricing implications of skewness. Boyer, Mitton, and Vorkink (2009) construct a cross-sectional model of expected idiosyncratic skewness and show that stocks with high expected idiosyncratic skewness have lower subsequent returns. However, constructing expected skewness for stock returns is difficult because the correct set of predictive variables, such as momentum and turnover, is not known precisely. Further, because expected idiosyncratic skewness is computed 5 years ahead of the variables, capturing the impact of short-term changes of expected skewness is difficult.[2] Using option data is a possible way to compute *ex ante* skewness without requiring a long history of data.[3] Following the methodology of Bakshi, Kapadia, and Madan (2003), option-implied risk-neutral skewness can capture the short-term changes of stock return predictability of skewness. To our knowledge, researchers have not examined the short-term time-varying return predictive power of skewness. In addition, because return predictability of skewness is influenced by the investors' skewness preference, we investigate changes in the expectations of investors' skewness preference.[4] Finally we interpret the results to understand the characteristics of option-implied skewness.

In this paper, we examine whether option-implied skewness, contains information that forecasts the cross-sectional expected stock returns, and whether the predictive power of return varies with market state and investor sentiment. Option-implied skewness has a negative relation between subsequent stock returns. The return predictive power of skewness remains even after controlling for firm-characteristic variables that are known to forecast stock returns such as idiosyncratic volatility, return reversal, momentum, market capitalization, book-to-market ratio, market beta, and the illiquidity measure. In addition, return predictability of

[1] Harvey and Siddique (2000) and Dittmar (2002) provide empirical results that stock returns' co-skewness with the market portfolio return is priced. Mitton and Vorkink (2007) and Barberis and Huang (2008) establish their models and show that stocks with high idiosyncratic skewness exhibit lower expected returns.

[2] Boyer, Mitton, and Vorkink (2009) denote that expected skewness premium has time-series variation, but they do not find which factors affect the skewness premium. We refer to short-term as one month in this article.

[3] Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003) show that risk-neutral skewness of stock returns can be calculated by using a set of daily option prices with different strike prices on that stock. Using Bakshi, Kapadia, and Madan (2003) risk-neutral skewness, Dennis and Mayhew (2002) and Conrad, Dittmar, and Ghysels (2013) examine cross-sectional stock return predictability of skewness.

[4] We determine the investors' skewness preference by analyzing the return predictability of skewness.

skewness is only significant during downturn market periods and high investor sentiment states.[5] Kumar (2009) and Fong and Toh (2014) also find investors' demand for lottery-like stocks increases during economic downturns or high investor sentiment periods. Thus, we conclude that the investors also regard high option-implied skewness stocks as lottery-like stocks. Our analysis suggests that option-implied skewness also has economic meanings not just a theoretically calculated measure.

We begin our analysis with daily option data to compute option-implied skewness. There are some advantages using option-implied skewness to predict expected stock returns. First, the use of option prices reduces the need for long time-series of stock data to estimate skewness of the returns distribution. In particular, option-implied skewness easily captures the changes in return predictive power of skewness during the periods when the expectation of investors' skewness preference is altered. Second, option prices are a market-based estimate of investors' expectations. Bates (1991), Rubinstein (1994), and Jackwerth and Rubinstein (1996) find that option prices contain the information of market participants. Thus, under the assumption that no-arbitrage rules hold between the options and stocks market, option prices contain the identical information of stock prices.[6] Third, options contain *ex ante* expectations of the stock returns distribution. The stock return predictive power of options data is caused by informed traders who choose the option market to trade first, and then they trade in the stock markets. (e.g. Chowdhry and Nanda (1991) and Easley, O'hara, and Srinivas (1998)).[7]

We additionally analyze whether the return predictability of skewness depends on the market state or not. Kumar (2009) shows that excess buy–sell imbalance (EBSI) for high skewness stocks is high when the market return is low. In other words, investors especially prefer high skewness stocks during bad market states because investors have a similar preference for high skewness stocks and state lotteries.[8] We separately investigate the return predictability of skewness during downturn markets and upturn markets. Our results confirm that the return predictability of skewness is significant during downturn markets.

The return predictability of skewness also depends on the sentiment of market participants. We proxy investor sentiment index for the University of Michigan consumer sentiment index (MCSI) following Lemmon

[5] We define an upturn (downturn) market when the market return is above (below) the risk-free rate and high (low) investor sentiment state when the MCSI is above (below) its median value.

[6] Ofek and Richardson (2003) and Battalio and Schultz (2006) say that option prices and the prices of underlying stocks did not diverge during the Internet bubble when eliminating options of stale price quotes. In section 2.1, we employ filters to avoid misleading prices of options.

[7]Bali and Hovakimian (2009), Cremers and Weinbaum (2010) , and Xing, Zhang, and Zhao (2010) also use a cross section of options data to show that option prices include predictive information about stock returns.

[8] Lottery studies explain that people find the tiny probability of a large payoff more attractive during bad economic conditions. Mikesell (1994) empirically shows that people are attracted more toward state lotteries during economic downturns.

and Portniaguina (2006). We use the MCSI because we can easily collect data after 2010.[9] Also, Fisher and Statman (2003) find a positive correlation between investor sentiment and consumer sentiment. We find that high skewness stocks exhibit significantly lower subsequent returns during high investor sentiment periods (i.e. levels of the MCSI above the median value). When the investor sentiment is high, investors are more optimistic about the future payoffs of high skewness stocks and the future returns of such stocks become low. Fong and Toh (2014) also argue that the lottery-like stocks exhibit low subsequent returns only during high investor sentiment periods.[10]

We compare the effect of the market return and the MCSI to return predictive power and further analyze the relation between them. The previous literature finds that the consumer sentiment is related to the macroeconomic conditions. Lemmon and Portniaguina (2006) argue that the MCSI is a good predictor of business cycle peaks and troughs and Bram and Ludvigson (1998) and Ludvigson (2004) find that consumer sentiment predicts future household spending. There are few papers analyzing the relation between market return and consumer sentiment, and so we examine the time-series relations between lagged market returns and the MCSI. The correlations between lagged market returns and the MCSI are higher than contemporaneous time of the two variables. We also find that the return predictability of skewness is significant during lagged upturn market periods.

The rest of the paper is organized as follows. In Section 2, we present the methodology to compute skewness and discuss the data and variables used in our analysis. In Section 3, we examine the predictive power of option-implied risk-neutral skewness on the cross-sectional stock returns using stock portfolios and cross-sectional regressions, respectively. In Section 4, we focus on testing whether the market state and investor sentiment really affect the stock return predictability of skewness. In Section 5, we compare the influence of the market return and MCSI to return predictability of skewness and investigate the time-series relation between the two values. We conclude in Section 6.

2. Data and Methodology

In this section we describe the data and the methodology to compute option-implied risk-neutral skewness. Risk-neutral skewness is computed by daily option data and the monthly firm-characteristic variables are

[9] The often used indicator for investor sentiment, the Baker and Wurgler (2006) investor sentiment index, is not available after 2010.

[10] They define the lottery-like stocks as high MAX stocks. MAX is defined as maximum daily returns (MAX) over the past month.

created by daily and monthly stock data.

2.1. Option-Implied Risk-Neutral Skewness

The daily option data are obtained from OptionMetrics. We begin with out-of-the-money (OTM) calls and puts option data for all stocks from 1996 to August 2014.[11] Only a few option-implied risk-neutral skewness are computed from January 1996 to June 1996. Finally, we choose our sample period as being from July 1996 to August 2014. Closing prices for options are constructed as the midpoint of the last bid-ask quotes for each day.

We eliminate bid-ask option pairs with missing quotes, or zero bids, as well as option prices violating arbitrage restrictions which is $\mathrm{C}_{i,t}(\tau; K_i) < \mathrm{S}_{i,t}$. As Bakshi, Kapadia, and Madan (2003) argue, the magnitude of the early exercise premium in OTM calls and puts is very small, we do not adjust for American option early exercise premium in our option prices.

In computing option-implied risk-neutral skewness, we only use option data which have at least two OTM calls and two OTM puts for each stock, day, and maturity.[12] In addition, calculating skewness is most accurate when we have the same numbers of OTM calls and puts for each stock, day, and maturity. If there are n OTM puts available on day *t* with maturity τ, we also require n OTM calls. However, if there are N (N > n) OTM calls available on day *t* with maturity τ, we retain the n OTM calls that have the most similar distance from stock price to strike as the OTM puts for which we have data. Then we eliminate the options for which there is no trading volume for each stock, day, and maturity. We also remove the options with closing prices less than 50 cents. The resulting set of the data consists of 10,944,976 daily observations across stocks and maturities over the time period July 1996 through August 2014.

To estimate option-implied risk-neutral skewness of the individual stocks, we use the results of Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003). Bakshi and Madan (2000) show that any payoff of an underlying security *i* can be calculated using the set of option prices with different strike prices on that security. They define $V_{i,t}(\tau)$ and $W_{i,t}(\tau)$ as the time *t* prices of τ-maturity quadratic and cubic contracts. Let E_t^Q represent the expectation operator under the risk-neutral measure, and let the τ -period continuously compounded return on the underlying asset *i*, $\mathrm{S_i}$, be $R_{i,t}(\tau) = \ln[\frac{S_i(t+\tau)}{S_i(\tau)}]$. The time *i* price of a quadratic and cubic contracts payoff received at time $t + \tau$ can be written as

[11] The reason for only using out-of-the-money calls and puts is that they reduce the early exercise premium of American options.

[12] Dennis and Mayhew (2002) prove that if there are complete observations on OTM calls with various strike prices, at least two observations of OTM puts reduce the bias to essentially zero.

$$V_{i,t}(\tau) = E_t^Q\left[e^{-r\tau}R_{i,t}(\tau)^2\right] \text{ and } \mathrm{W}_{i,t}(\tau) = E_t^Q\left[e^{-r\tau}R_{i,t}(\tau)^3\right] \tag{1}$$

where r is the risk-free rate.

Bakshi, Kapadia, and Madan (2003) show that the τ-period risk-neutral return skewness, $\mathrm{SKEW}_{i,t}^Q(\tau)$ is defined by

$$\mathrm{SKEW}_{i,t}^Q(\tau) = \frac{e^{r\tau}W_{i,t}(\tau) - 3\mu_{i,t}(\tau)e^{r\tau}V_{i,t}(\tau) + 2\mu_{i,t}(\tau)^3}{\left[e^{r\tau}V_{i,t}(\tau) - \mu_{i,t}(\tau)^2\right]^{3/2}}. \tag{2}$$

The expressions for $V_{i,t}(\tau)$, $V_{i,t}(\tau)$, and $\mu_{i,t}(\tau)$ are given by

$$\mathrm{V}_{i,t}(\tau) = \int_{S_{i,t}}^{\infty} \frac{2\left(1-\ln\left(\frac{K_i}{S_{i,t}}\right)\right)}{K_i^2} C_{i,t}(\tau; K_i)\mathrm{dK}_i \; + \; \int_0^{S_{i,t}} \frac{2\left(1-\ln\left(\frac{K_i}{S_{i,t}}\right)\right)}{K_i^2} P_{i,t}(\tau; K_i)dK_i, \tag{3}$$

$$\begin{aligned} \mathrm{W}_{i,t}(\tau) = {} & \int_{S_{i,t}}^{\infty} \frac{6\ln\left(\frac{K_i}{S_{i,t}}\right) - 3\left[\ln\left(\frac{K_i}{S_{i,t}}\right)\right]^2}{K_i^2} C_{i,t}(\tau; K_i)dK_i \\ & + \int_0^{S_{i,t}} \frac{6\ln\left(\frac{K_i}{S_{i,t}}\right) - 3\left[\ln\left(\frac{K_i}{S_{i,t}}\right)\right]^2}{K_i^2} P_{i,t}(\tau; K_i)dK_i, \end{aligned} \tag{4}$$

$$\mu_{i,t}(\tau) = \mathrm{e}^{r\tau} - 1 - \frac{e^{r\tau}V_{i,t}(\tau)}{2} - \frac{e^{r\tau}W_{i,t}(\tau)}{6} - \frac{e^{r\tau}X_{i,t}(\tau)}{24}. \tag{5}$$

where $\mathrm{C}_{i,t}(\tau; K_i)$ and $\mathrm{P}_{i,t}(\tau; \mathrm{K}_i)$ are the time *t* prices of the call and put options written on the underlying stock $\mathrm{S}_{i,t}$ with a strike price $\mathrm{K}_{i,t}$ and expiration τ periods from time *t*. As equations (3) and (4) show, the procedure involves using a weighted sum of OTM options across varying strike prices to calculate the prices of payoffs related to risk-neutral return skewness. Following Dennis and Mayhew (2002), we use the trapezoidal approximation in equations (3) and (4) using our discrete data.

2.2. Firm-Characteristic Variables and Investor Sentiment Index

We obtain underlying stock return data from CRSP and accounting data from COMPUSTAT with common shares outstanding. We take the risk-free rates from the bank discount yields on secondary market 3-month Treasury bills taken from Federal Reserve Report H.15 and market returns are the CRSP monthly value-weighted index. We calculate the following firm-characteristic variables associated with underlying stocks that are widely known to forecast the cross-sectional stock returns.

Idiosyncratic Volatility (IDVOL)

Following Ang, Hodrick, Xing, and Zhang (2006), *IDVOL* is idiosyncratic volatility that is defined as the standard deviation of the residuals obtained from regressing stock's excess returns on the Fama and French (1993) three factors. That is, $IDVOL_{i,t} = \sqrt{var(\varepsilon_{i,t})}$ for each stock i in month t. $\varepsilon_{i,t}$ is obtained by following regression.

$$\mathrm{R}_{i,d} - r_{f,d} = \alpha_i + \beta_{MKT,i}MKT_d + \beta_{SMB,i}SMB_d + \beta_{HML,i}HML_d + \varepsilon_{i,t}. \quad (1)$$

where $\mathrm{R}_{i,d}$ is the return on stock i on day d, $\mathrm{r}_{f,d}$ is risk-free rate on day d. MKT_d, SMB_d, and HML_d are the daily Fama and French (1993) three factors.

Short-Term Reversal (REV)

Following Jegadeesh (1990) and Lehmann (1990), we compute short-term reversal, $REV_{i,t}$, for each stock in month t as the return on the stock over the previous month $t-1$.

Momentum (MOM)

Following Jegadeesh and Titman (1993), we construct the momentum variable $MOM_{i,t}$, for each stock i in month t, which is defined as the cumulative return on the previous 11 months avoiding the short-term reversal effect. That is, $MOM_{i,t}$ is the cumulative return from month $t-12$ to month $t-2$.

Size (SIZE)

$SIZE_{i,t}$ is measured as the natural logarithm of the market value of equity (stock price multiplied by the number of shares outstanding in millions of dollars) at the end of month t for each stock i.

Book-to-Market Ratio (BM)

We use the Fama and French (1992) methodology to compute a firm's book-to-market ratio in month t. To calculate $BM_{i,t}$, we use the market value of its equity at the end of December of the previous year and the book value of common equity for the firm's latest fiscal year ending in the prior calendar year. The book-to-market ratio for firm i is then calculated by dividing the market value by the book value.

Market Beta (BETA)

Following Dimson (1979), we extend the CAPM market beta to take into account nonsynchronous trading. To make monthly $BETA_{i,t}$ for firm i in month t, we use daily frequency of the individual firm and market return data. The regression equation is as follows:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1} - r_{f,d-1}) + \beta_{2,i}(R_{m,d} - r_{f,d}) \\ + \beta_{3,i}(R_{m,d+1} - r_{f,d+1}) + \varepsilon_{i,d}. \quad (7)$$

where $R_{m,d}$ is measured by the CRSP daily value-weighted index. The sum of the estimated slope coefficients, $\widehat{\beta_{1,t}} + \widehat{\beta_{2,t}} + \widehat{\beta_{3,t}}$, is then the market beta of stock *i* in month *t*.

Illiquidity (ILLIQ)

We adopt the Amihud (2002) illiquidity measure. In detail, for each stock *i* in month *t*, we construct $ILLIQ_{i,t}$ as being the monthly average of the ratio of the absolute daily stock to its daily dollar trading volume, $ILLIQ_{i,t} = |R_{i,t}|/VOL_{i,t}$, where $R_{i,t}$ is the return on stock *i* in month *t* and $VOL_{i,d}$ is the daily trading volume of stock i in 100 million dollars.

< Insert Table 1 Here >

In Table 1, we present summary statistics for the monthly firm-specific variables. In Panel A, we report descriptive statistics for the stocks that have option-implied skewness. Panel B reports descriptive statistics for all common shares outstanding in the CRSP. Panel C reports the correlations between the variables. There are different patterns between Panel A and Panel B. The firms in Panel A have higher momentum return, larger firm size, smaller book-to-market-ratio, larger beta, and lower illiquidity measure compared with the firms in Panel B. What this means is that the firms in Panel A have highly auto-correlated returns, include a large proportion of big firms, a lot of growth firms, high return sensitivity to the market return, and have plenty of liquidity. Thus, if the stocks have option-implied skewness, or stocks with more than four OTM calls and puts options, they generally tend to be large market capitalization and actively traded firms.

< Insert Figure 1 Here >

In Figure 1, we display the time variation of the ratio of our sample stocks to all stocks in CRSP. The straight line presents the ratio of the market capitalization and the dashed line presents the ratio of the average number of monthly stocks. The ratio of the market capitalization is always larger than the ratio of the number of stocks which means that our sample stocks tend to be large firms.

The average market capitalization ratio of our sample stocks to all stocks in CRSP is 18% and varies from 2% to 47% during the data period. The ratio tends to be high in recent years, especially after 2003, which means that recent data have more stocks listed on the option market, and thus we can collect more information about option-implied skewness after 2003. The ratio of the number of stocks tends to have similar pattern with the market capitalization. While the average ratio of the market capitalization or number looks like being too low to represent the whole stock market, our purpose is not to seek characteristics of the entire stock market. Our primary goal is to find characteristics of option-implied skewness and, so we only examine the stocks that have option-implied skewness.

We use the University of Michigan consumer sentiment index as a proxy for investor sentiment index to find the relation between investor sentiment and the return predictability of skewness.[13] One reason why we use the MCSI as the proxy for investor sentiment is that MCSI is easily obtainable. We are able to collect it through our whole sample period (July 1996 to August 2014).[14] In addition, we could not obtain the BW index (Baker and Wurgler (2006) investor sentiment index), which is commonly used to measure investor sentiment index, after 2010. As shown in Figure 1, the periods from 2010 to 2014 contains lots of information about skewness, and thus we should include the periods with the MCSI.

Some of the literature say investor sentiment is related to asset pricing anomalies. Fong and Toh (2014) find that previous extreme stock return (MAX), the maximum daily return within a month, is negatively correlated with the next month's stock return when the BW index is high. In addition, Stambaugh, Yu, and Yuan (2012) conclude that most of the 11 anomalies are stronger (its long-short strategy is significantly profitable) following high levels of investor sentiment. They adopt investor sentiment index using both the BW index and MCSI, and both measures show similar results.

3. Option-Implied Risk-Neutral Skewness and the Cross-Sectional Stock Returns

In this section we describe the detailed methodology to create monthly option-implied risk-neutral skewness, *SKEW*. We report the tercile portfolios return in Table 2 Panel A, to compare the results with Conrad, Dittmar, and Ghysels (2013), and we report the quintile portfolios return for the rest of our analysis.

3.1. Portfolio Sorts

[13] Some studies (e.g., Lemmon and Portniaguina (2006)) find that investor sentiment is correlated with consumer sentiment.
[14] Monthly MCSI data can be downloaded from http://www.sca.isr.umich.edu/tables.html.

Each day, with computed $\mathrm{SKEW}_{i,t}^{Q}(\tau)$, we sample the OTM calls and puts on individual stocks that have maturities greater than 7 days but less than 30 days. We then apply the Bakshi, Kapadia, and Madan (2003) procedure outlined in the previous section to estimate monthly option-implied risk-neutral skewness. Before we create monthly skewness, we winsorize the outliers. Within the daily frequency, a number of firms present extreme values of skewness and they could cause bias, and so we remove observations that have cross-sectional skewness in the top 1% and bottom 1% each day.

Following Bakshi, Kapadia, and Madan (2003), we average the daily estimates of skewness for each stock over 1 month. Finally, each firm in our sample has a single observation of skewness for each month through from July 1996 to August 2014. We then form quintile portfolios ranked by *SKEW*, which is rebalanced every month. In Table 2, we show returns and firm-characteristics of the tercile and quintile portfolios. Portfolio 1 contains stocks with the lowest *SKEW* in the previous month and Portfolio 3 (5) includes stocks with the highest *SKEW* in the previous month. We equally weight the returns and the firm-characteristics in each tercile (quintile) portfolio.

< Insert Table 2 Here >

In Table 2 Panels A and B, the first column shows the raw returns of the portfolios for the subsequent month. In the next column, we report the characteristic-adjusted returns of the portfolios. Following Daniel and Titman (1997) and Daniel, Grinblatt, Titman, and Wermers (1997), we similarly calculate for the size and book-to-market adjusted returns. For each individual firm return, we assign the 25 Fama and French (1993) size and book-to-market portfolios to which it belongs. We subtract the returns of the matched Fama and French (1993) portfolios from the individual stock returns and form equally weighted resulting returns with the *SKEW* sorted portfolios. In the third column, we report risk-adjusted returns using the Fama and French (1993) market, size, and book-to-market factors. In the remaining columns, we display the monthly *SKEW* and characteristics for the tercile (quintile) portfolios. The characteristic variables are idiosyncratic volatility, short-term reversal, momentum, size, book-to-market ratio, market beta, and illiquidity. The last row of Table 2 presents the Newey and West (1987) t-statistics of the null hypothesis that the difference in the third (fifth) and first terciles (quintiles) is zero with 3 lags.

3.2. Return Predictability of the Skewness Sorted Portfolios

In Table 2 Panel A, the mean return, Char-Adj return, and FF3 alpha of stocks in tercile 1 exhibit 1.12%, 0.24%, and 0.35% per month, respectively, and they monotonically decrease to 0.34%, −0.50%, and −0.83% per month for stocks in tercile 3. The differences in mean return, Char-Adj return, and FF3 alpha between tercile 3 and 1 is −0.78%, −0.74%, and −0.83% per month respectively with highly significant Newey and West (1987) t-statistics (−2.56, −2.52, and −2.87). Conrad, Dittmar, and Ghysels (2013) also find stocks with high skewness exhibit low subsequent returns in a sample period from 1996 through 2005. In Panel B, we also present the returns of the quintile portfolios. We only report the returns of the quintile portfolios in the lasting sections, because the literature shows that a negative relation between stock return skewness and subsequent return is largely generated by the highest skewness portfolios among the quintile or decile portfolios (e.g. Boyer, Mitton, and Vorkink (2009) and Bali, Cakici, and Whitelaw (2011)).[15] We find similar results using quintile portfolios. The mean returns, Char-Adj returns, and FF3 alpha of the second to fourth quintiles tend to be flat and significant declines in returns occur between the fourth and fifth quintiles. We are not able to see this pattern using tercile portfolios. The differences in the mean returns, Char-Adj returns, and FF3 alpha between quintile 5 and 1 is −1.03%, −0.99%, and −1.10% per month respectively with highly significant Newey and West (1987) t-statistics (−2.58, −2.59, and −2.94). The returns spread between quintile 5 and 1 is larger than that between tercile 3 and 1.

3.3. Firm-Characteristics of Skewness Sorted Portfolios

Table 2 Panels A and B also present firm-characteristics of the tercile and quintile skewness sorted portfolios. There are no discernible large differences in size and book-to-market ratio across the terciles and quintiles. However, differences in idiosyncratic volatility, short-term reversal, momentum, beta, and illiquidity across terciles and quintiles exhibit some patterns. We find a positive relation between the idiosyncratic volatility and skewness which corresponds to the previous literature. (Barberis and Huang (2008), Ang, Hodrick, Xing, and Zhang (2009), Boyer, Mitton, and Vorkink (2009)) In Panel B, the idiosyncratic volatility of the low skewness portfolio is 0.022 and 0.031 for the high skewness portfolio. The idiosyncratic volatility monotonically increases as the skewness increases and previous returns tend to decrease as the skewness increases. The momentum returns increase and the market betas decline as the skewness increases. In the

[15] Bali, Cakici, and Whitelaw (2011) construct portfolios based on MAX which is the highest daily stock return in the previous month.

literature, short-term reversal, momentum, size, book-to-market ratio, and market beta have a negative, positive, negative, and positive relation with subsequent stock returns, respectively. (Jegadeesh (1990), Fama and French (1992), Jegadeesh and Titman (1993)) While in our sample, the above-mentioned variables present the opposite relations with subsequent returns or have no clear pattern. In other words, the above-mentioned firm-characteristic variables cannot explain negative relation between skewness and subsequent returns.[16] Our sample, having option-implied skewness, shows different pattern of the firm-characteristics compared with the whole common stocks in CRSP. Our sample exhibits relatively large momentum returns, large market capitalization, small book-to-market ratio, and large beta as reported in Table 1. Thus, firm-characteristic variables that have a return predictability in the overall stock market would not have significant return predictive power in our sample. The illiquidity monotonically increases as the skewness increases, which corresponds to Amihud (2002)'s finding of a positive return–illiquidity relation. In Panel B, the illiquidity shows an increasing pattern from quintile 2 to quintile 5 except for the low skewness quintile. Interestingly, the illiquidity steeply increases in quintile 5 and looks similar to the returns which substantially decrease in quintile 5. Idiosyncratic volatility and illiquidity possibly explain the negative relation between skewness and subsequent return. In the next section, we further analyze the effect of return predictability of skewness and simultaneously control for idiosyncratic volatility and illiquidity.

3.4. Fama-MacBeth Cross-Sectional Regressions

The analysis in Table 2 indicates that some firm-characteristics are playing a role in predicting subsequent stock returns when the portfolios are sorted by skewness. Further analysis is required to control for the effect of firm-characteristic variables.[17] We now conduct firm-level Fama and MacBeth (1973) regressions of subsequent stock returns on skewness and other firm-characteristic variables. Following the equation for each month *t*,

$$\mathrm{R}_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot SKEW_{i,t} + \lambda_{2,t} \cdot X_{i,t} + \varepsilon_{i,t+1} \tag{8}$$

where $\mathrm{R}_{i,t+1}$ is the realized return on stock *i* in month $t+1$, $SKEW_{i,t}$ is the skewness on stock *i* in month *t*, and $X_{i,t}$ is a collection of firm-characteristic control variables observable at month *t* for stock *i*. In Table 3, we report the average cross-sectional coefficients and the Newey and West (1987) adjusted t-statistics with 3 lags from

[16] Fama and MacBeth (1973) regressions are conducted in Section 3.4 to precisely examine the effect of the other firm-characteristics.

[17] We especially control for the effect of idiosyncratic volatility and illiquidity.

equation (8) across stocks i at time t. The cross-sectional regressions are run monthly from July 1996 to August 2014.

< Insert Table 3 Here >

In column 1, in the univariate regression of skewness (*SKEW*), the coefficient is negative and statistically significant at the 1% level. Corresponding to previous section, stocks with low skewness tend to exhibit high returns in the subsequent month. In columns 2 to 4, we additionally include idiosyncratic volatility (*IDVOL*) and illiquidity (*ILLIQ*) as control variables with SKEW. Whether we include the idiosyncratic volatility alone (column 2), the illiquidity alone (column 3), or both the idiosyncratic volatility and illiquidity together (column 4), the coefficients of skewness remain statistically significant at either the 1% or the 5% level. In column 2 and 3, following Amihud (2002) and Ang, Hodrick, Xing, and Zhang (2009), the coefficients of idiosyncratic volatility and illiquidity are both negative and statistically significant at the 1% level, while in column 4, the coefficient of idiosyncratic volatility loses its significance. Also in column 4, the coefficient of illiquidity remains significant t-statistics at the 5% level. In column 5, when skewness and the seven control variables are added to the regression, the coefficient of *SKEW* remains negative and statistically significant at the 5% level, while some of the relations between the control variables and subsequent returns are generally not significant. The coefficient of the idiosyncratic volatility (*IDVOL*) remains negative but statistically insignificant. The coefficients of short-term reversal (*REV*), momentum (*MOM*), book-to-market (*BM*), and market beta (*BETA*) are all insignificantly different from zero and their signs are the opposite to that reported in the earlier literature, because we use skewness computable stocks, our sample has biased firm-characteristics, as displayed in Table1. The coefficients of the market capitalization (*SIZE*) and illiquidity are both negative and only the coefficient of illiquidity is significantly different from zero. These results confirm the robustness of the return predictive power of skewness.

4. The Effect of Market Returns and Investor Sentiment.

So far we have examined the return predictability of option-implied skewness with data period from July 1996 to August 2014. In this section we divide the sample into upturn and downturn markets or high and low investor sentiment periods.[18] The significance level of the return differences of high and low skewness is different between the divided sample periods.

4.1. Return Predictability of Skewness; the Effect of Market Return

We separate the sample months with respect to the level of market return. We define an upturn (downturn) market when $R_{m,t}$ is higher (lower) than $R_{f,t}$.

< Insert Table 4 Here >

In Table 4, we present returns and alphas of the quintile portfolios sorted by skewness. We separately show the results when the market return is above the risk-free rate ($R_{m,t} \geq R_{f,t}$; upturn market) and below the risk-free rate ($R_{m,t} < R_{f,t}$; downturn market). In both Panels A and B, the first column shows equally weighted return of portfolios over the subsequent month. In the second column, we display characteristic-adjusted return of the portfolios over the next month. In the last column, we report risk-adjusted returns using the Fama and French (1993) market, size, and book-to-market factors. The last row presents the Newey and West (1987) t-statistics with 3 lags.

In Table 4 Panel A, we show the mean return, Char-Adj return, and FF3 alpha of quintiles when the market return is above the risk-free rate (upturn market). There are 93 months of upturn market periods in our sample. The mean return of quintile 4 (1.90% per month) is the highest return among quintiles. The mean return of quintile 5 (0.75% per month) is the lowest return among quintiles. There are no notable patterns of return within the five portfolios. The Char-Adj return and FF3 alpha have a similar pattern to the mean return. All differences of the mean returns, Char-Adj returns, and FF3 alpha between quintiles 5 and 1 exhibit negative values but their t-statistics are not all significant. Only the significance level of the FF3 alpha is just above the 10% level which is not enough to say skewness predicts the return in the subsequent month. We could say that the return predictability of skewness might disappear in an upturn market.

Table 4 Panel B displays the different patterns of return. There are 125 months of a downturn market in our

[18] Pettengill, Sundaram, and Mathur (1995), Ang, Chen, and Xing (2006), and Alles and Murray (2013) show that market return affects risk premium. They define the sample upturn and downturn markets and report different predictability of betas among these samples. Lemmon and Portniaguina (2006), Stambaugh, Yu, and Yuan (2012), and Fong and Toh (2014) divide the sample into high and low sentiment periods and they examine when the anomalies become stronger.

sample and thus the number of downturn market months slightly exceeds the number of upturn market months. The mean return of quintile 1 (0.69% per month) is the highest among quintiles. The mean returns of quintiles 2 and 3 have almost the same magnitude as those of the mean returns (0.47% and 0.52% per month, respectively), and the mean returns of quintiles 4 and 5 are largely decreasing (0.05% and −0.41% per month, respectively). We could say the mean return in the subsequent month is decreasing as the skewness is increasing. The mean return differential between the high and low skewness portfolios is −1.1% per month, and so also negative, and its t-statistics is statistically significant at the 5% level (−2.08**)**. The second and third column, denoted Char-Adj return and FF3 Alpha, also present a similar pattern of the relation between skewness and subsequent return. Table 2 Panels A and B imply that a negative relation between skewness and the subsequent return remains when the market declines although the difference in the mean returns between high and low skewness portfolios is only significantly different from 0 in Panel B (downturn market periods).

The previous literature has shown similar results. Kumar (2009) documents that the excess buy–sell imbalance (EBSI) for high skewness stocks is high when the market return is low.[19] High EBSI means people prefer to invest in high skewness stocks. He also says that aggregate demand for lottery-type stocks and state lotteries should be correlated.[20] In particular, like state lotteries, investors are likely to exhibit a high preference for lottery-type stocks during bad economic times or low market return periods. Boyer, Mitton, and Vorkink (2009) show that expected skewness risk premium exhibits temporal variation and that the expected skewness risk premium is positively related to the level, dispersion, and predicted power of expected skewness. When the level, dispersion, and predicted power of expected skewness is high, there are greater opportunities for skewness-preferring investors to realize their preference for high skewness stocks with upside potential. While expected skewness is constructed by several firm-specific variables, the time variation of the expected skewness risk premium is not economically intuitive. It is possible that firm-characteristic variables, such as turnover ratio, could be affected by time varying economic conditions. We examine the time variation of the return predictability of skewness in a different way. Aggregating the studies of Kumar (2009) and Boyer, Mitton, and Vorkink (2009), we suppose that the time variation of return predictability of skewness might depend on the market return. When the market return is low, a higher demand for high skewness stocks strengthens the return predictive power for these stocks. In other words, there is a negative relation between the return predictive power of skewness and the market return as shown in Table 4 Panels A and B. In the next section, we further

[19] The measure EBSI captures the change in investors' bullishness toward lottery-type stocks relative to the change in their bullishness toward other remaining stocks.

[20] They define lottery-type stocks as those that exhibit high skewness, high volatility, and a low price.

examine the effects of the market return on skewness premium following Fama and MacBeth (1973) cross-sectional regression and the Pettengill, Sundaram, and Mathur (1995) methodology.

4.2. Fama-MacBeth Cross-sectional Regressions; the Effect of Market Return

As mentioned in 4.1, we also divide the sample months into two groups to estimate the cross-sectional regressions. We denote an upturn (downturn) market when $\mathrm{R}_{m,t}$ is higher (lower) than $\mathrm{R}_{f,t}$. In Table 5, we run the following firm-level cross-sectional regressions,

$$\mathrm{R}_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \delta_t \cdot SKEW_{i,t} + \lambda_{2,t} \cdot (1 - \delta_t) \cdot SKEW_{i,t} + \lambda_{3,t} \cdot X_{i,t} + \varepsilon_{i,t+1} \quad (9)$$

where $\mathrm{R}_{i,t+1}$ is the realized return on stock *i* in month *t+1*, $SKEW_{i,t}$ is the skewness on stock *i* in month *t*, and $X_{i,t}$ is a collection of firm-characteristic control variables observable at month *t* for stock *i*. When the market return is above the risk-free rate ($\mathrm{R}_{m,t} \geq \mathrm{R}_{f,t}$), we assign δ_t as equal to 1, and below the risk-free rate ($\mathrm{R}_{m,t} < \mathrm{R}_{f,t}$), we denote δ_t as equal to 0. The above regression equation is conducted for each month *t* to estimate $\lambda_{1,t}$ and $\lambda_{2,t}$ depending on the magnitude of the market return. If high skewness stocks exhibit low subsequent returns only when market return is high (low), $\widehat{\lambda_1}$ ($\widehat{\lambda_2}$) would be negative and statistically significant. In Table 5, we report the average cross-sectional coefficients and the Newey and West (1987) adjusted t-statistics with 3 lags from equation (9). The cross-sectional regressions are run monthly from July 1996 to August 2014. We have 93 upturn market months and 125 downturn market months.

< Insert Table 5 Here >

In Table 5 column 1, we include $SKEW_{i,t}$ which is an independent variable in the regressions. The estimated coefficients of the product of market return dummies and *SKEW*, $\widehat{\lambda_1}$ and $\widehat{\lambda_2}$, are −0.003 and −0.014, respectively. The sum of these coefficients is obviously the same as the coefficient on *SKEW* in Table 3 column 1. Their t-statistics are −0.79 and −3.12, and only $\widehat{\lambda_2}$ is statistically significant at the 1% level. This result clearly demonstrates that high skewness predicts a low subsequent return when the market return is below the risk-free rate. In Table 5 column 2, we additionally include firm-specific variables as independent variables. We have not included the product of the dummy variables and firm-specific variables because we are only interested in seeing the effect of market return on the return predictability of skewness. The coefficients of the product of

δ_t and $SKEW_{i,t}$ are −0.001 and −0.007, respectively. The sum of these values is also the same as the coefficient of $SKEW$ in Table 3 column 5, and their t-statistics are −0.35 and −1.98. Even though the absolute value of the t-statistics is smaller than that in column 1, $\widehat{\lambda_2}$ remains the significance level at the 5%. According to Table 5, we propose that return predictability of skewness largely comes from the downturn market periods.

4.3. Return predictability of skewness; the effect of investor sentiment

We separate the sample months with respect to the level of investor sentiment index (MCSI). The MCSI consists of the survey questions of 500 households. It asks people how much their economic situations or current buying conditions have improved. Because market return and the MCSI have different economic meanings, the high market return months do not correspond with the high MCSI months.

In Table 6, we present the returns of quintile portfolios sorted by skewness. We split our sample into a high investor sentiment period (MCSI is above its median value) and a low investor sentiment period (MCSI is below its median value). In both Panels A and B, the first column shows the equally weighted skewness-sorted portfolio returns. In the second column, we show the characteristic-adjusted returns of the portfolios over the next month. In the last column, we report the risk-adjusted returns using the Fama and French (1993) market, size, and book-to-market factors. The last row presents the Newey and West (1987) t-statistics with 3 lags.

< Insert Table 6 Here >

In Panel A, we show the mean return, Char-Adj return, and FF3 alpha of the quintiles when the MCSI is above its median value. There are 109 high investor sentiment months in our sample period. The mean return of quintile 1 (1.13% per month) is the highest among the quintiles. Except for quintile 2, the mean returns decrease as the skewness increases. The mean returns of quintiles 4 and 5 exhibit a remarkable decrease from 0.66% to −0.42% per month. The mean returns differential between the high and low skewness portfolios is obviously negative and it is statistically different from zero with t-statistics of −2.21. In columns 2 and 3, the Char-Adj return and FF3 alpha also present a similar pattern. The Char-Adj return and FF3 alpha difference between the high and low skewness portfolios have the t-statistics of −2.17 and −2.14, respectively, and are statistically significant at the 5% level. From Table 6 Panel A, we conclude that high skewness predicts a low subsequent mean return only during high investor sentiment periods.

In Panel B, there are different patterns in the relation between skewness and subsequent returns. There are 109 low investor sentiment months in our sample. The mean return of quintiles 1, 2, and 4 are of almost the same magnitude (1.07%, 1.06%, and 1.00% per month, respectively). The mean return of quintile 5 (0.57% per month) is the lowest among the quintiles while a decreasing magnitude of the return between quintiles 4 and 5 is not seen. The difference in the mean return between the quintiles 5 and 1 (−0.5% per month) is small and its t-statistics is not statistically significant. The Char-Adj return shows similar patterns with respect to the mean return. The difference in the Char-Adj return between quintile 5 and 1 (−0.52% per month) is also small and it is not significantly different from zero. However, FF3 alpha exhibits a quite different pattern. The difference in the FF3 alpha between quintiles 5 and 1 (−0.80% per month) is larger than that of the mean return and the Char-Adj return and its t-statistics is statistically significant at the 5% level. From Panel B, we cannot conclude that skewness predicts subsequent stock returns just by the results of the FF3 alpha difference. Thus, the return predictability of skewness would disappear in the low investor sentiment periods. In summary, Table 6 implies that the negative relation between the skewness and subsequent return remains during high investor sentiment periods. In other words, investors are seeking high skewness stocks only when their sentiment is high. The investors are more optimistic about the future payoffs of high skewness stocks when investor sentiment is high.

In Panel C, we present simple firm-level cross-sectional regressions as follows

$$\mathrm{R}_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \delta_t \cdot SKEW_{i,t} + \lambda_{2,t} \cdot (1-\delta_t) \cdot SKEW_{i,t} + \varepsilon_{i,t+1} \tag{10}$$

where $\mathrm{R}_{i,t+1}$ is the realized return on stock *i* in month *t+1*, $SKEW_{i,t}$ is the skewness on stock *i* in month *t*. We assign δ_t as being equal to 1 when the MCSI is above its median and assign δ_t as being equal to 0 when the MCSI is below its median. The above regression equation is conducted for each month *t* to estimate $\lambda_{1,t}$ and $\lambda_{2,t}$ depending on the investor sentiment.

In Panel C, we report the average cross-sectional coefficients and the Newey and West (1987) adjusted t-statistics with 3 lags from equation (10). The cross-sectional regressions are run monthly from July 1996 to August 2014. There are 109 months of high sentiment periods and 109 months of low sentiment periods. The estimated coefficients of the product of δ_t and $SKEW_{i,t}$, $\widehat{\lambda_1}$ and $\widehat{\lambda_2}$, are −0.013 and −0.004, respectively, and their t-statistics are −2.36 and −1.46, and thus only $\widehat{\lambda_1}$ is statistically significant. We confirm that high skewness predicts low subsequent returns only when the MCSI is above its median.

5. Market Return Versus Investor Sentiment

5.1. Jointly controlling the effect of the market state and investor sentiment

In this section, we examine the return predictability of skewness in the four sample periods which are divided by a two-way classification of the sample months by market state and investor sentiment. Together with the market return and the investor sentiment index criterion, we have four combinations: an upturn market with high or low investor sentiment periods and a downturn market with high or low investor sentiment periods. We could verify which factors mostly affect the return predictability of skewness between market state and investor sentiment. In Table 7, we find that the return predictability of skewness is significant following periods of a downturn market, regardless of the level of the investor sentiment index. Thus, investors consider high skewness stocks as lottery-like stocks rather than investors optimistically assigning future positive payoffs during high sentiment periods.

< Insert Table 7 Here >

In Table 7, we present the results of the Fama and MacBeth (1973) cross-sectional regressions. The dependent variable is subsequent month stock returns, and the independent variable is *SKEW*. We show the average slope coefficients of *SKEW* and its t-statistics. Columns 1 to 4 display the four periods which are divided the above classification. More specifically, column 1 (2) shows the upturn market with high (low) investor sentiment periods and column 3 (4) shows the downturn market with high (low) investor sentiment periods. Each column, 1 to 4, has 35, 57, 74, and 51 sample months, respectively. In columns 1 and 2, the coefficients of *SKEW* are −0.016 and −0.001, respectively, and their t-statistics are statistically insignificant. In columns 3 and 4, the coefficients of *SKEW* are −0.03 and −0.017, respectively, and their t-statistics are statistically significant at the 5% and 10% level. Similar to the prior results, sample months within a downturn market and in high sentiment periods have the highest absolute value of the coefficient and t-statistics of *SKEW*. In Table 7, the results show that the return predictability of skewness is significant when the market return in the prior month is below the risk-free rate (downturn market). Thus, the return predictability of skewness is affected by the market return regardless of the investor sentiment.

5.2. The Relation Between the Market Return and the Investor Sentiment Index

To summarize the analysis in section 5.1, the return predictability of skewness is significant when the market return is low and the investor sentiment index is high. In simple terms, however, the market return and the investor sentiment index might have a positive correlation.[21] If the market return and investor sentiment index exhibit positive and large time-series autocorrelation, their influence on the return predictability of skewness might be the same. However, the contrasting results suggest that another type of relation between the market return and the investor sentiment index exists. In this section, we examine the relation between lagged market return and investor sentiment index. The lagged market returns have higher correlation coefficients with the investor sentiment index compared with the market return and the investor sentiment index within the same time period.

< Insert Table 8 Here >

In Table 8, we display the Pearson correlation coefficients between the lagged market return and the MCSI. The market return has a correlation of 0.079 with the investor sentiment index. We also see that the MCSI has a larger correlation with the lagged market return than with the simultaneous market return. The MCSI in month t and the market return in months $t-1$, $t-2$, and $t-3$ have correlations of 0.157, 0.185, and 0.159 respectively. That is, the investor sentiment index in month t has a positive correlation with the market return in months $t-1$ to $t-5$, so we could say that the market return precedes the investor sentiment index. It is well known in macroeconomics that the market return precedes the macroeconomic factors such as unemployment rate, the inflation rate, or the producer price index. The investor sentiment might exhibit similar characteristic with the macroeconomic factors. It is possible that although the market return is high in the preceding month, the investor sentiment index might not be high in the same month. Several months later the market return increases and investors finally feel optimistic about economic conditions.

In Table 9, we present the results of the Fama and MacBeth (1973) cross-sectional regressions where the dependent variable is the subsequent month stock return and the independent variable is *SKEW*. We show the average slope coefficients of *SKEW* and its t-statistics. In columns 1 and 2, we separate the sample periods with respect to the market return in month $t-2$. If the market return in month $t-2$ is above the risk-free rate in month $t-2$, we conduct a regression of the raw return in month $t+1$ on the *SKEW* in month t in column 1. In another

[21] The market return, GDP growth rate, and other macroeconomic factors would be positively related to the consumer sentiment index. When the market return is high or the macroeconomic indicators show good economic conditions, the consumers tend to be more optimistic.

case, in column 2, if the market return in month $t-2$ is below the risk-free rate in month $t-2$, we conduct the same procedures. In columns 3 to 6, we conduct similar regressions while we separate sample periods regarding month $t-3$ or $t-4$ of the market return and the risk-free rate. Each column, 1 to 6, has sample including 91, 126, 90, 127, 89, and 128 months respectively.

< Insert Table 9 Here >

In Table 9, it is of interest that there are statistically significant coefficients of *SKEW* when the market return in month $t-2$ or $t-3$ is above the risk-free rate. If the market return in month $t-2$ or $t-3$ is below the risk-free rate, however, the coefficients on the *SKEW* would not be statistically significant. In Table 9 columns 1 through 4, in contrast to Tables 4 and 5, the return predictability of skewness is powerful when month $t-2$ or $t-3$ is an upturn market. This is because the market return in month $t-2$ or $t-3$ affects the investor sentiment index in month t. As already seen in Table 8, the investor sentiment index in month t would be high if the market return in month $t-2$ or $t-3$ is high. Thus, Table 6 and Table 9 imply that the effect of the market return in month $t-2$ or $t-3$ to return predictive power of skewness is similar with the investor sentiment index in month t.

The lagged market return may influence not only the investor sentiment index but also the other macroeconomic factors. It is also possible that the return predictive power of the skewness is affected by the market return in month $t-2$ or $t-3$ which comes from the effect of other macroeconomic factors and not by the investor sentiment index. Future research might examine how other macroeconomic factors affect the return predictability of skewness.

6. Conclusion

We show that the option-implied risk-neutral skewness is important in explaining the cross-sectional expected stock returns. In addition, we analyze whether the return predictability of skewness is influenced by the market state and investor sentiment. Using option data from July 1996 to August 2014, we calculate the risk-neutral skewness for individual stocks following the methodology of Bakshi, Kapadia, and Madan (2003).

We find a negative cross-sectional relation between skewness and the subsequent month of stock returns. When tercile and quintile portfolios are formed based on skewness, the spread in the average subsequent months of returns and alphas between the low and high skewness portfolios is −0.74% to −1.1% per month and is statistically significant. That is, option-implied skewness reflects investors' preference for positive skewness. This result is consistent with the results of Conrad, Dittmar, and Ghysels (2013). We also check robustness to control for firm-characteristic variables, such as idiosyncratic volatility, illiquidity, return reversal, momentum, size, book-to-market, and market beta in the regressions. We estimate firm level Fama and MacBeth (1973) cross-sectional regressions where the dependent variable is the subsequent month of stock returns and the independent variable is *SKEW*. We find that the coefficients of *SKEW* remain negative and statistically significant with the different types of regression.

We examine the influence of market state and investor sentiment on the return predictability of skewness. In other words, we confirm that the market state and investor sentiment could change the investors' skewness preference. First, we split the sample periods into two groups regarding the level of the market return and the MCSI. There are 93 upturn market months and 125 downturn market months and 109 months of high investor sentiment periods and 109 months of low investor sentiment periods. For each of the four periods, we form skewness sorted quintile portfolios. In upturn market and downturn market periods, the return spreads between the high and low skewness portfolios are approximately −1% per month each but it is only statistically significant during downturn market months. Furthermore, the return spread for high sentiment periods corresponds to −1.5% per month and −0.5% per month for low sentiment periods. Only the return spread for high sentiment period is statistically significant at the 5% level. We then similarly conduct Fama and MacBeth (1973) cross-sectional regressions and the coefficients of *SKEW* are statistically significant following downturn market and high investor sentiment periods. We also jointly divide our sample into four groups regarding the market return and investor sentiment index and we find that the return predictability of skewness is only significant during downturn market periods. Thus, investors recognize high skewness stocks as lottery-like stocks which leads to time-variation in the return predictive power of skewness.

Finally, we examine the relation between the market return and MCSI. The correlation between 2 or 3 months lagged market return and the MCSI is higher than the correlation between the contemporaneous months of the market return and MCSI. That is, the market return is the leading indicator of the MCSI. We also find the return predictability of skewness remains when 2 or 3 month lagged market return is above the risk-free rate because if the market return in month $t-2$ or $t-3$ is high, the MCSI in month t might also be high.

In conclusion, we find that investors similarly recognize the high option-implied skewness stocks and lottery-like stocks. In other words, our research suggests that the Bakshi, Kapadia, and Madan (2003) skewness measure has identical economic meanings with historical return skewness. This *ex ante* option-implied skewness measure can capture the time-varying investors' preference for positivly skewed returns. It might be also interesting that future studies should investigate the economic meanings of Bakshi, Kapadia, and Madan (2003) volatility or kurtosis.

Table 1

Summary Statistics for Firm-Specific Variables

Panel A contains the univariate statistics for the monthly firm-specific variables that are used in our analysis. Panel B also describes firm-specific variables that covers all firms in CRSP. Data are obtained from CRSP, Compustat, and OptionMetrics. $SKEW_{i,t}$ is monthly average of daily estimates of the option-implied risk-neutral skewness for each stock i in month t. We construct daily option-implied risk-neutral skewness following the procedure in Bakshi, Kapadia, and Madan (2003) using options data of out-of-the-money(OTM) puts and calls. $IDVOL_{i,t}$ is the monthly estimates of idiosyncratic volatility using Ang, Hodrick, Xing, and Zhang (2006) methodology in month t. $REV_{i,t}$ is short-term reversal following Jegadeesh (1990) and Lehmann (1990), for return on each stock i on the previous month $t-1$. $MOM_{i,t}$ is the momentum for each stock cumulative return over the previous 11 months from $t-11$ to $t-1$. $SIZE_{i,t}$ is the natural logarithm of the market value of each stock i at the end of month t. $BM_{i,t}$ is the book-to-market ratio following Fama and French (1992). $BETA_{i,t}$ is the firm's beta with the value weighted returns of the whole stocks in CRSP following Dimson (1979). $ILLIQ_{i,t}$ is Amihud (2002) illiquidity variable which is the ratio of the absolute monthly stock return to its 100 million dollars trading volume over month t. Panel C contains the Pearson correlation coefficients of monthly firm-specific variables that are described in Panel A. The sample consists of 10,944,976 option-implied risk-neutral skewness over the time period July 1996 through August 2014. Monthly stocks data contains the period July 1996 through August 2014, for sample lengths of 218 months.

Panel A: The Firms That have Option-Implied Risk-Neutral Skewness

	Mean	P25	Median	P75	STD
$SKEW_{i,t}$	−0.175	−0.241	−0.100	0.010	0.414
$IDVOL_{i,t}$	0.027	0.013	0.021	0.035	0.021
$REV_{i,t}$	0.017	−0.077	0.009	0.094	0.204
$MOM_{i,t}$	0.618	−0.014	0.294	0.731	1.517
$SIZE_{i,t}$	15.176	14.211	15.156	16.119	1.306
$BM_{i,t}$	0.385	0.148	0.293	0.513	0.354
$BETA_{i,t}$	1.560	0.706	1.386	2.237	1.716
$ILLIQ_{i,t}$	0.158	0.014	0.039	0.128	0.476

Panel B: All Firms in CRSP

	Mean	P25	Median	P75	STD
$IDVOL_{i,t}$	0.030	0.014	0.022	0.037	0.028
$REV_{i,t}$	0.012	−0.070	0.002	0.075	0.194
$MOM_{i,t}$	0.139	−0.234	0.044	0.333	0.809
$SIZE_{i,t}$	12.443	10.925	12.358	13.861	2.048
$BM_{i,t}$	0.737	0.306	0.547	0.895	0.911
$BETA_{i,t}$	0.875	0.025	0.791	1.679	2.047
$ILLIQ_{i,t}$	256.212	0.254	3.106	49.154	1362.362

Panel C: Correlation Coefficients (Our Sample)

	$SKEW_{i,t}$	$IDVOL_{i,t}$	$REV_{i,t}$	$MOM_{i,t}$	$SIZE_{i,t}$	$BM_{i,t}$	$BETA_{i,t}$	$ILLIQ_{i,t}$
$SKEW_{i,t}$	1.00							
$IDVOL_{i,t}$	0.22	1.00						
$REV_{i,t}$	0.00	0.09	1.00					
$MOM_{i,t}$	0.09	0.22	−0.01	1.00				
$SIZE_{i,t}$	0.00	−0.39	0.05	−0.13	1.00			
$BM_{i,t}$	−0.07	−0.19	0.01	−0.02	0.04	1.00		
$BETA_{i,t}$	0.07	0.15	0.00	0.08	−0.10	−0.05	1.00	
$ILLIQ_{i,t}$	0.05	0.21	−0.01	0.02	−0.42	0.00	0.04	1.00

Table 2

Tercile and Quintile Portfolios of Stocks Sorted by Skewness

Panels A and B describe summary statistics for tercile (quintile) portfolios which are sorted by option-implied risk-neutral skewness. Portfolio 1 contains stocks with the lowest *SKEW* in the previous month and Portfolio 3 (5) includes stocks with the highest *SKEW*. We equally weight stocks in each tercile (quintile) portfolio and rebalance every month. The first column of each panel presents monthly mean returns. The second column presents characteristic-adjusted returns, following Daniel and Titman (1997), for each firm, that returns in excess of the 5×5 Fama and French (1993) size and book-to-market portfolio to which it belongs. The third column presents Fama and French (1993) three factor alphas. The next nine columns show the average firm-characteristic variables of each tercile (quintile) portfolio. *SKEW* is the monthly average of daily estimates of the option-implied risk-neutral skewness for each stock *i* on month *t*. We construct daily option-implied risk-neutral skewness following the procedure in Bakshi, Kapadia, and Madan (2003) using options data of out-of-the-money(OTM) puts and calls. *IDVOL* is monthly estimates of idiosyncratic volatility using Ang, Hodrick, Xing, and Zhang (2006) methodology in month *t*. *REV* is the short-term reversal following Jegadeesh (1990) and Lehmann (1990), for return on each stock *i* on the previous month $t-1$. *MOM* is the momentum for each stock cumulative return over the previous 11 months from $t-11$ to $t-1$. *SIZE* is the natural logarithm of the market value of each stock *i* at the end of month *t*. *BM* is the book-to-market ratio following Fama and French (1992). *BETA* is the firm's beta with the value weighted returns of the whole stocks in CRSP following Dimson (1979). *ILLIQ* is Amihud (2002) illiquidity variable which is the ratio of the absolute monthly stock return to its 100 million dollars trading volume over month *t*. The row 3−1 (5−1) presents the difference in average mean returns, Char-Adj returns, and FF3 alphas between the high and low skewness tercile (quintile). The final row presents Newey and West (1987) t-statistics of the null hypothesis that the difference in the third and first terciles (quintiles) is zero. Monthly stocks data contains the period July 1996 through August 2014, for sample lengths of 218 months.

Panel A: Tercile Portfolios of Stocks Sorted by Skewness

	Mean Return	Char-Adj Return	FF3 Alpha	*SKEW*	*IDVOL*	*REV*	*MOM*	*SIZE*	*BM*	*BETA*	*ILLIQ*
1 (Low)	1.122%	0.239%	0.350%	−0.458	0.023	0.029	0.556	15.268	0.387	1.450	0.110
2	0.697%	−0.162%	−0.054%	−0.127	0.026	0.026	0.674	15.261	0.370	1.611	0.099
3 (High)	0.340%	−0.502%	−0.480%	0.092	0.030	0.020	0.693	14.891	0.386	1.776	0.179
3−1	−0.782%	−0.741%	−0.830%								
t-stat.	−2.56	−2.52	−2.87								

Panel B: Quintile Portfolios of Stocks Sorted by Skewness

	Mean Return	Char-Adj Return	FF3 Alpha	*SKEW*	*IDVOL*	*REV*	*MOM*	*SIZE*	*BM*	*BETA*	*ILLIQ*
1 (Low)	1.103%	0.239%	0.341%	−0.595	0.022	0.028	0.515	15.214	0.403	1.406	0.124
2	0.746%	−0.123%	−0.009%	−0.235	0.024	0.030	0.639	15.346	0.366	1.546	0.087
3	0.848%	−0.009%	0.077%	−0.125	0.026	0.024	0.664	15.272	0.364	1.618	0.100
4	0.831%	−0.058%	0.056%	−0.035	0.028	0.025	0.688	15.092	0.377	1.717	0.128
5 (High)	0.077%	−0.747%	−0.760%	0.167	0.031	0.018	0.696	14.772	0.397	1.781	0.209
5−1	−1.026%	−0.987%	−1.101%								
t-stat.	−2.58	−2.59	−2.94								

Table 3

Fama-MacBeth Regressions

This table reports the results of firm-level Fama and MacBeth (1973) cross-sectional regressions of stock returns on the monthly variables. The model is

$$\mathrm{R}_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot SKEW_{i,t} + \lambda_{2,t} \cdot X_{i,t} + \varepsilon_{i,t+1}$$

where $\mathrm{R}_{i,t+1}$ is the return for stock *i* in month *t+1*. $SKEW_{i,t}$ is the skewness of the option-implied risk-neutral skewness for stock *i* in month *t*. $X_{i,t}$ indicates firm-characteristic variables observed at the end of month *t*. These variables are monthly idiosyncratic volatility (*IDVOL*), short-term return reversal (*REV*), momentum return (*MOM*), log of market capitalization (*SIZE*), book-to-market ratio (*BM*), market beta (*BETA*), and Amihud (2002) illiquidity measure (*ILLIQ*). The average slope coefficients and Newey and West (1987) t-statistics (in parentheses) are reported. The last row shows the average adjusted R^2 values. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The regressions are estimated each month over the time period July 1996 through August 2014.

	(1)	(2)	(3)	(4)	(5)
Constant	0.005	0.013***	0.009	0.013**	0.053*
	(0.87)	−2.61	−1.52	−2.54	(1.83)
SKEW	**−0.017*** **	**−0.015*** **	**−0.012** **	**−0.010** **	**−0.009* **
	(−2.96)	(−2.95)	(−2.29)	(−2.06)	(−1.71)
IDVOL		**−0.283** **		−0.08	−0.318
		(−1.97)		(−0.56)	(−1.54)
REV					0.039
					(1.49)
MOM					−0.003
					(−0.50)
SIZE					−0.003
					(−1.57)
BM					−0.003
					(−0.25)
BETA					−0.000
					(−0.11)
ILLIQ			**−0.063** **	**−0.066** **	**−0.060* **
			(−2.46)	(−2.16)	(−1.88)
Adjusted R^2	0.002	0.027	0.02	0.042	0.119

Table 4

SKEW Sorting Portfolios: Effect of Market Return

This table describes the returns and alphas of quintile portfolios which are sorted by option-implied risk-neutral skewness. We separately show results when the market return is high or low. We denote upturn (downturn) market which monthly market return exceeds (is below) the risk-free rates. Market returns are the CRSP monthly value-weighted index and risk-free rate is the yield of secondary market 3-month Treasury bills taken from Federal Reserve Report H.15. Panel A shows portfolio returns with an upturn market and Panel B show portfolio returns with downturn market. In both Panels portfolio 1 contains the stocks with the lowest skewness in the previous month and portfolio 5 includes the stocks with the highest skewness in the previous month. We equally weight stocks in each quintile portfolio and rebalance every month. The first column of both panels presents the average monthly returns. The second column presents characteristic-adjusted returns, following Daniel and Titman (1997), for each firm that returns in excess of the 5×5 Fama and French (1993) size and book-to-market portfolio to which it belongs. The third column presents Fama and French (1993) three factor alphas. There are 93 (125) months of upturn (downturn) markets. The row 5−1 presents the difference in average raw returns, Char-Adj returns, and FF3 alpha between the high and low skewness quintiles. The last row presents Newey and West (1987) t-statistics. Monthly stocks data contains the period July 1996 through August 2014, for sample lengths of 218 months.

Panel A: Upturn Market

	Mean Return	Char-Adj Return	FF3 Alpha
1(Low)	1.671%	0.300%	0.135%
2	1.117%	−0.195%	−0.269%
3	1.292%	−0.004%	−0.184%
4	1.899%	0.514%	0.490%
5(High)	0.745%	−0.693%	−0.983%
5−1	−0.926%	−0.993%	−1.117%
t-stat.	−1.41	−1.54	−1.68

Panel B: Downturn Market

	Mean Return	Char-Adj Return	FF3 Alpha
1(Low)	0.686%	0.195%	0.406%
2	0.472%	−0.070%	0.197%
3	0.521%	−0.012%	0.263%
4	0.045%	−0.479%	−0.186%
5(High)	−0.414%	−0.787%	−0.686%
5−1	−1.100%	−0.982%	−1.093%
t-stat.	−2.08	−1.92	−2.16

Table 5

Fama-Macbeth Regressions with Market Return Dummies

This table reports the results of firm-level Fama-MacBeth (1973) regressions of stock returns on the monthly skewness and dummy variables. The model is

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \delta_t \cdot SKEW_{i,t} + \lambda_{2,t} \cdot (1 - \delta_t) \cdot SKEW_{i,t} + \lambda_{3,t} \cdot X_{i,t} + \varepsilon_{i,t+1}$$

where $R_{i,t+1}$ is the return for stock *i* in month *t+1*. $SKEW_{i,t}$ is the skewness of the option-implied risk-neutral skewness for stock *i* in month *t*. When the market return is above the risk-free rate in month t, we assign δ_t as being equal to 1 and below the risk-free rate, we denote δ_t as being equal to 0. $X_{i,t}$ indicates firm-characteristic variables observed at the end of month *t*. These variables are monthly idiosyncratic volatility (*IDVOL*), short-term return reversal (*REV*), momentum return (*MOM*), log of market capitalization (*SIZE*), book-to-market ratio (*BM*), market beta (*BETA*), and Amihud (2002) illiquidity measure (*ILLIQ*). The first column shows the result of regression where the independent variable is *SKEW*. The second column displays the results of the regression when we additionally include firm-characteristic variables as independent variables. In the table, the average slope coefficients and Newey and West (1987) t-statistics (in parentheses) are reported. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The last row shows the average adjusted R^2 values. The regressions are estimated each month over the time period July 1996 through August 2014.

	(1)	(2)
Constant	0.005	0.053*
	(0.87)	(1.83)
$\delta \cdot SKEW$	−0.003	−0.001
	(−0.79)	(−0.35)
$(1-\delta) \cdot SKEW$	**−0.014*** **	**−0.007** **
	(−3.12)	(−1.98)
IDVOL		−0.318
		(−1.54)
REV		0.039
		(1.49)
MOM		−0.003
		(−0.50)
SIZE		−0.003
		(−1.57)
BM		−0.003
		(−0.25)
BETA		−0.000
		(−0.11)
ILLIQ		**−0.060***
		(−1.88)
Adjusted R^2	0.002	0.119

Table 6

SKEW Sorting Portfolios: Effect of Investor Sentiment

This table describes the returns and alphas of quintile portfolios which are sorted by option-implied risk-neutral skewness. We separately show results when the consumer sentiment index (MCSI) is high or low. We denote high (low) MCSI when it is above (below) its median value. MCSI is the Michigan Research Survey Consumer Sentiment Index which consists of 500 survey questions. Panel A shows the portfolio returns with high MCSI and Panel B shows the portfolio returns with low MCSI. In Panels A and B, portfolio 1 contains stocks with the lowest skewness in the previous month and portfolio 5 includes stocks with highest skewness in the previous month. We equally weight stocks in each quintile portfolio and rebalance every month. The first column of both panels present the average monthly returns. The second column presents characteristic-adjusted returns, following Daniel and Titman (1997), for each firm that returns in excess of the 5×5 Fama and French (1993) size and book-to-market portfolio to which it belongs. The third column presents Fama and French (1993) three factor alphas. There are 109 (109) months of high (low) MCSI months. The row 5−1 presents the difference in average raw returns, Char-Adj returns, and FF3 alpha between the high and low skewness quintiles. The last row presents Newey and West (1987) t-statistics. Panel C reports the results of firm-level Fama and MacBeth (1973) regressions of stock returns on the monthly skewness and dummy variables. The model is:

$$\mathrm{R}_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \delta_t \cdot SKEW_{i,t} + \lambda_{2,t} \cdot (1 - \delta_t) \cdot SKEW_{i,t} + \varepsilon_{i,t+1}$$

where $\mathrm{R}_{i,t+1}$ is the return for stock *i* in month *t+1*. $SKEW_{i,t}$ is the skewness of the option-implied risk-neutral skewness for stock *i* in month *t*. When the MCSI is above its median value in month t, we assign δ_t as being equal to 1 and below its median value, we denote δ_t as being equal to 0. The column shows the results of the above regression. In the table, the average slope coefficients and Newey and West (1987) t-statistics (in parentheses) are reported. Significance at the 1%, 5%, and 10% level is indicated by $***$, $**$, and $*$, respectively. The last row shows the average adjusted R^2 values. The regressions are estimated each month over the time period July 1996 through August 2014.

Panel A: High Investor Sentiment

	Mean Return	Char-Adj Return	FF3 Alpha
1(Low)	1.132%	0.502%	1.025%
2	0.438%	−0.222%	0.306%
3	0.819%	0.134%	0.754%
4	0.662%	0.025%	0.513%
5(High)	−0.416%	−0.952%	−0.518%
5−1	−1.547%	−1.454%	−1.543%
t-stat.	−2.21	−2.17	−2.14

Panel B: Low Investor Sentiment

	Mean Return	Char-Adj Return	FF3 Alpha
1(Low)	1.074%	−0.026%	0.022%
2	1.056%	−0.024%	−0.148%
3	0.877%	−0.152%	−0.405%
4	1.002%	−0.141%	−0.224%
5(High)	0.574%	−0.540%	−0.780%
5−1	−0.500%	−0.515%	−0.802%
t-stat.	−1.24	−1.34	−2.26

Panel C: Fama-Macbeth Regressions with MCSI Dummies

Constant	0.005
	(0.87)
$\delta \cdot SKEW$	**−0.013****
	(−2.36)
$(1-\delta) \cdot SKEW$	−0.004
	(−1.46)
Adjusted R^2	0.002

Table 7

Joint Effect of Market Return and MCSI

This table presents the results of the Fama and MacBeth (1973) cross-sectional regressions where the dependent variable is the subsequent month stock return, and the independent variable is *SKEW*. We show the average slope coefficients of *SKEW* and its t-statistics. In column 1 through 4, we present the results of our divided sample where the criterion satisfies the following condition. Together with the level of market return and MCSI, we have four combinations; upturn market with a high or low investor sentiment state and downturn market with a high or low investor sentiment state. More specifically, column 1 (2) shows the upturn market with high (low) investor sentiment periods and column 3 (4) shows the downturn market with high (low) investor sentiment periods. Each column 1 to 4 has sample lengths of 35, 57, 74, and 51 months respectively. In the table, the average slope coefficients and Newey and West (1987) t-statistics (in parentheses) are reported. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The last row shows the average adjusted R^2 values. The regressions are estimated each month over the time period July 1996 through August 2014.

	R_m>R_f and *MCSI*>0	R_m>R_f and *MCSI*<0	R_m<R_f and *MCSI*>0	R_m<R_f and *MCSI*<0
Intercept	0.006	0.018***	0.002	−0.004
	(0.45)	(3.55)	(0.16)	(−0.32)
SKEW	−0.016	−0.001	**−0.030****	**−0.017***
	(−0.84)	(−0.09)	(−2.47)	(−1.74)
Adjusted R^2	0.003	0.002	0.005	−0.002

Table 8

Pearson Correlation Coefficient

This table displays the Pearson correlation coefficients between lagged market return and MCSI. Market returns are the CRSP monthly value-weighted index and MCSI is the Michigan Research Survey Consumer Sentiment Index. Monthly market returns and MCSI contain the period July 1996 through August 2014, for sample lengths of 218 months.

	Rm_t	Rm_{t-1}	Rm_{t-2}	Rm_{t-3}	Rm_{t-4}	Rm_{t-5}	Rm_{t-6}	Rm_{t-7}	Rm_{t-8}	Rm_{t-9}	Rm_{t-10}	Rm_{t-11}	$MCSI_t$
Rm_t	1.000												
Rm_{t-1}	0.109	1.000											
Rm_{t-2}	−0.031	0.111	1.000										
Rm_{t-3}	0.070	−0.032	0.113	1.000									
Rm_{t-4}	0.045	0.069	−0.032	0.112	1.000								
Rm_{t-5}	−0.028	0.045	0.069	−0.031	0.112	1.000							
Rm_{t-6}	−0.058	−0.028	0.045	0.069	−0.031	0.112	1.000						
Rm_{t-7}	0.031	−0.061	−0.026	0.044	0.068	−0.031	0.113	1.000					
Rm_{t-8}	0.059	0.034	−0.063	−0.024	0.045	0.067	−0.031	0.116	1.000				
Rm_{t-9}	−0.053	0.058	0.035	−0.064	−0.025	0.045	0.068	−0.033	0.118	1.000			
Rm_{t-10}	0.028	−0.054	0.059	0.034	−0.065	−0.024	0.045	0.066	−0.031	0.117	1.000		
Rm_{t-11}	0.026	0.026	−0.052	0.058	0.034	−0.064	−0.024	0.043	0.069	−0.033	0.116	1.000	
$MCSI_t$	**0.079**	**0.157**	**0.185**	**0.159**	**0.143**	**0.151**	**0.117**	**0.119**	**0.105**	**0.136**	**0.103**	**0.093**	**1.000**

Table 9

Fama-Macbeth Regressions with Lagged Market Returns

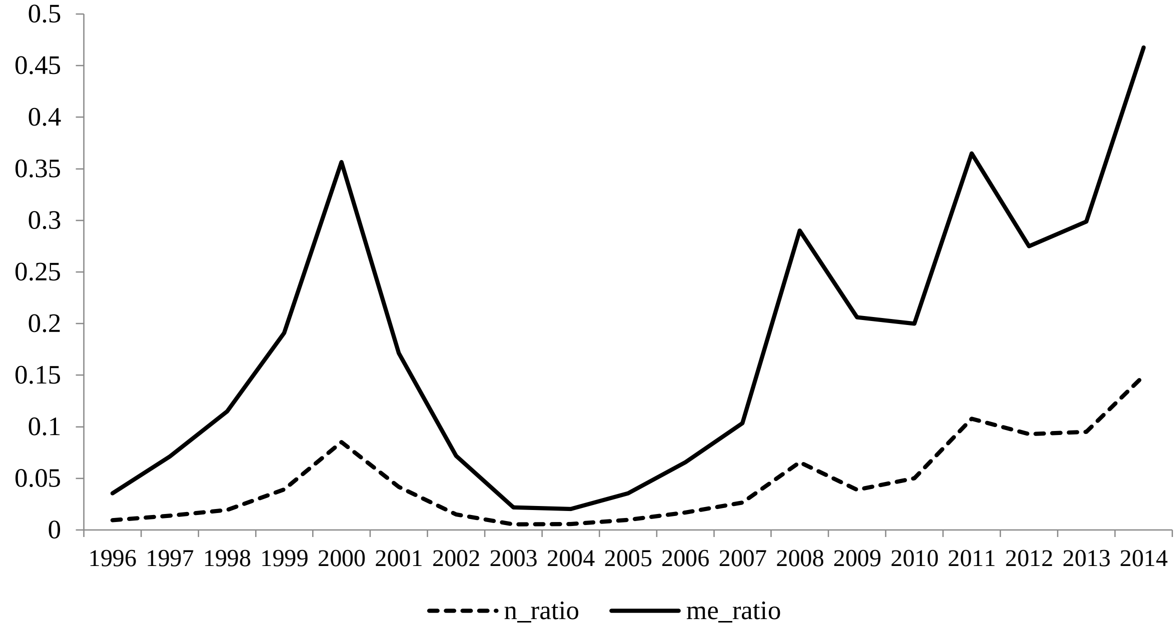
This table presents the results of the Fama and MacBeth (1973) cross-sectional regressions where the dependent variable is the subsequent month stock return and the independent variable is *SKEW*. In columns 1 and 2, we separate our sample with respect to the market return in month *t−2*. If the market return in month *t−2* month is above the risk-free rate in month t−2, we conduct a regression with the raw return in month *t+1* on *SKEW* in month *t* in column 1. Another case, in column 2, if the market return in month *t−2* is below the risk-free rate in month *t−2*, we conduct same procedures. In columns 3 to 6, we conduct similar regressions while we separate sample periods regarding the market return in month *t−3* or *t−4* and the risk-free rate. Each column 1 to 6 has sample lengths with 91, 126, 90, 127, 89, and 128 months respectively. In the table, the average slope coefficients and Newey and West (1987) t-statistics (in parentheses) are reported. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The last row shows the average adjusted R^2 values. The regressions are estimated each month over the time period July 1996 through August 2014.

	$Rm_{t-2} > Rf_{t-2}$	$Rm_{t-2} < Rf_{t-2}$	$Rm_{t-3} > Rf_{t-3}$	$Rm_{t-3} < Rf_{t-3}$	$Rm_{t-4} > Rf_{t-4}$	$Rm_{t-4} < Rf_{t-4}$
Intercept	−0.000	0.009	0.008	0.003	−0.008	0.015*
	(−0.04)	(1.11)	(1.22)	(0.40)	(−1.04)	(1.80)
SKEW	**−0.029*****	−0.008	**−0.023****	−0.013	**−0.018****	**−0.016****
	(−2.93)	(−1.22)	(−2.45)	(−1.38)	(−2.03)	(−2.04)
Adjusted R2	0.004	0.001	−0.003	0.006*	0.000	0.004
	(1.38)	(0.42)	(−1.03)	(1.97)	(0.01)	(1.46)

Figure 1

Time Variation of the Ratios of Our Sample Stocks to All Stocks in CRSP

The straight line presents the ratio of the market capitalization and the dashed line presents the ratio of the average number of monthly stocks. The ratios are estimated each month over the time period July 1996 through August 2014.



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