What Does Individual Option Volatility Smirk Tell Us About Future Equity Returns?

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Abstract

The shape of the volatility smirk has significant cross-sectional predictive power for future equity returns. Stocks exhibiting the steepest smirks in their traded options underperform stocks with the least pronounced volatility smirks in their options by 10.9% per year on a risk-adjusted basis. This predictability persists for at least six months, and firms with the steepest volatility smirks are those experiencing the worst earnings shocks in the following quarter. The results are consistent with the notion that informed traders with negative news prefer to trade out-of-the-money put options, and that the equity market is slow in incorporating the information embedded in volatility smirks.

JEL classification: G11, G12, G14

Keywords: stock return predictability, option-implied volatility smirks, cross-sectional asset pricing

I. Introduction

How information becomes incorporated into asset prices is one of the fundamental questions in finance. Due to distinct characteristics of different markets, informed traders may choose to trade in certain markets, and information is likely to be incorporated into asset prices in these markets first. If other markets fail to incorporate new information quickly, we might observe lead-lag relation between asset prices among different markets. In this paper, we use option price data from OptionMetrics to demonstrate that option prices contain important information for the underlying equities. In particular, we focus on the predictability and information content of volatility smirks, defined as the difference between the implied volatilities of out-of-the-money (OTM hereafter) put options and the implied volatilities of at-the-money (ATM hereafter) call options. We show that option volatility smirks are significant in predicting future equity returns in the cross-section. Our analysis also sheds light on the nature of the information embedded in volatility smirks.

The pattern of volatility smirks is well known for stock index options and has been examined in numerous papers. For instance, Pan (2002) documents that the volatility smirk for an S&P 500 index option with about 30 days to expiration is roughly 10% on a median volatile day. Bates (1991) argues that the set of index call and put option prices across all exercise prices gives a direct indication of market participants' aggregate subjective distribution of future price realizations. Therefore, OTM puts become unusually expensive (compared to ATM calls), and volatility smirks become especially prominent before big negative jumps in price levels, for example, during the year preceding the 1987 stock market crash. In an option pricing model, Pan (2002) incorporates both a jump risk premium and a volatility risk premium[1] and shows that investors' aversion toward negative jumps is the driving force for the volatility smirks. For OTM put options, the jump risk premium component represents 80% of total risk premium, while the premium is only 30% for OTM calls. Put differently, investors tend to choose OTM puts to express their worries concerning

[1] Many other papers also include both jump and volatility processes for index option pricing models, e.g., Duffie, Singleton, and Pan (2000) and Broadie, Chernov, and Johannes (2007), among others.

possible future negative jumps. Consequently, OTM puts become more expensive before large negative jumps.

In this article, we focus on individual stock options rather than on stock index options. We first document the prevalent existence of volatility smirks in individual stock options, which is consistent with previous literature (see Bollen and Whaley (2004), Bates (2003), and Garleanu, Pedersen, and Poteshman (2007)). From 1996 to 2005, more than 90% of the observations for all firms with listed options exhibit positive volatility smirks, with a median difference between OTM put and ATM call-implied volatilities being roughly 5%. Next, we demonstrate that the implied volatility smirks exhibit economically and statistically significant predictability for future stock returns. Similar to Bates' (1991) and Pan's (2002) arguments based on index options, higher volatility smirks in individual options should reflect a greater risk of large negative price jumps.[2] For our sample period from 1996 to 2005, stocks with steeper volatility smirks underperform those with flatter smirks by 10.90% per year on a risk-adjusted basis using the Fama and French (1996) three-factor model. This return predictability is robust to controls of various cross-sectional effects, such as size, book-to-market, idiosyncratic volatility and momentum.

To understand the nature of the information embedded in volatility smirks, we examine whether the predictability persists or reverses quickly. We find that the predictability of the volatility skew on future stock returns is persistent for at least six months. We also investigate the relation between volatility smirks and future earnings shocks. We find that stocks with the steepest volatility smirks are those stocks experiencing the worst earnings shocks in the following quarter. Our results indicate that the information in volatility smirks is related to firm fundamentals.

[2] To be precise, the volatility skew contains at least three levels of information: the likelihood of a negative price jump, the expected magnitude of the price jump, and the premium that compensates investors for both the risk of a jump and the risk that the jump could be large. Separating the three levels of information is beyond the current paper, and here we summarize the three levels of information as the risk of a large negative price jump.

It is not necessarily true that volatility skew should predict underlying stock returns. For instance, Heston (1993) develops an option pricing model with stochastic volatility, under the assumption that there is no arbitrage between the options market and the stock market. This model is able to generate volatility skew, but volatility skew in this model does not predict underlying stock returns, because the information sets of both options market and stock market are identical, and there is no information flow between the two markets. Conrad, Dittmar, and Ghysels (2007) examine implied volatility, skewness, and kurtosis using risk-neutral density function under the same no-arbitrage assumption. Different from the above two papers, we focus on the information embedded in volatility smirks without assuming equity market and options market have identical information sets. In a different setting, Gârleanu, Pedersen, and Poteshman (2007) construct a demand-based option pricing model. In their model, competitive risk-averse intermediaries cannot perfectly hedge their option positions, and thus demand for an option affects its price. In this new equilibrium, Gârleanu, Pedersen, and Poteshman (2007) find a positive relationship between option expensiveness measured by implied volatility and end-user demand. To put their model in our perspective, the end-user might have information advantage which might lead to higher demand for particular option contracts. This in turn affects the expensiveness of options measured by option implied volatility, and possibly predicts future stock returns. Thus, the findings in this paper are consistent with the equilibrium model of Gârleanu, Pedersen, and Poteshman (2007).

Our paper contributes to the literature that examines the linkage between the options market and the stock market at firm level. This literature is vast, and we only include several papers that are closely related. Easley, O'Hara, and Srinivas (1998) provide empirical evidence that option volume (separated by buyer-initiated and seller-initiated) can predict stock returns. Ofek, Richardson, and Whitelaw (2004) use individual stock options in combination with the rebate rate spreads to examine deviation from put-call parity and the existence of arbitrage opportunity between stock and options market. They find the deviation from put-call parity and rebate rate spreads are significant predictors of future stock returns. Chakravarty, Gulen, and Mayhew (2004) investigate the contribution of options market to price discovery and find that for their sample of 60 firms over five years, the options market's contribution to price discovery is about 17% on average. Cao, Chen, and Griffin (2005) find that prior to takeover announcements, call volume imbalances are strongly correlated with next-day stock returns. Finally, Pan and Poteshman (2006) show that put-call ratios by newly initiated trades have significant predictability for equity returns, which indicates informed trading in the options market.

Our work differs from previous studies along several dimensions. First, we are the first to examine the predictability and the information content of volatility smirks of individual stock options. Intuitively, OTM put is a natural place for informed traders with negative news to place their trades. Thus, the shape of volatility smirks might reflect the risk of negative future news. Previous literature has mostly focused on information contained in option volume. For instance, Pan and Poteshman (2006), Cao, Chen, and Griffin (2005) and Chan, Chung, and Fong (2002) investigate whether volume from the options market carries predictive information for the equity market. Chakravarty, Gulen, and Mayhen (2004) and Ofek, Richardson, and Whitelaw (2004) both use option price information in predicting equity returns, but neither of these studies examine volatility smirks. Second, our results shed light on the nature of the informational content of volatility smirks. The literature has documented that option prices as well as other information in the options market predict movements in the underlying securities. It is natural to ask whether the predictability is due to informed traders' information about fundamentals. We find that the information embedded in volatility smirks is related to future earnings shocks, in the sense that firms with the steepest volatility smirks have the worst earnings surprises. Finally, in order to examine the speed at which markets adjust to public information, we develop trading strategies based on past volatility smirks and examine risk-adjusted returns of these trading strategies over different holding periods. Pan and Poteshman (2006) find that publicly observable option signals are able to predict stock returns for only the next one or two trading days, and the stock prices subsequently reverse. They conclude that it is the private information that leads to predictability. In contrast, we find no quick reversals of the stock price movements following publicly observable volatility smirks. In fact, the predictability from volatility smirks persists for at least six months.

The remainder of the paper is organized as follows. Section II describes our data. Section III summarizes empirical results on the predictability of the option price information for equity returns. Section IV investigates the information content of volatility smirks. Section V discusses related research questions, and Section VI concludes.

II. Data

Our sample period is from January 1996 to December 2005. Option data are from OptionMetrics, which provides end-of-day bid and ask quotes, open interests, and volumes. It also computes implied volatilities and option Greeks for all listed options using the binomial tree model. More details about the option data can be found in the data appendix. Equity returns, general accounting data, and earnings forecast data are from CRSP, COMPUSTAT, and IBES, respectively.

We calculate our implied volatility smirk measure for firm *i* at week *t*, $\mathrm{SKEW}_{i,t}$, as the difference between the implied volatilities of OTM puts and ATM calls, denoted by $\mathrm{VOL}_{i,t}^{\mathrm{OTMP}}$ and $\mathrm{VOL}_{i,t}^{\mathrm{ATMC}}$, respectively. That is,

$$\mathrm{SKEW}_{i,t} = \mathrm{VOL}_{i,t}^{\mathrm{OTMP}} - \mathrm{VOL}_{i,t}^{\mathrm{ATMC}}. \tag{1}$$

A put option is defined as OTM when the ratio of strike price to the stock price is lower than 0.95 (but higher than 0.80), and a call option is defined as ATM when the ratio of strike price to the stock price is between 0.95 and 1.05.[3] To ensure that the options have enough liquidity, we only include options with time to expiration between 10 and 60 days. We compute the weekly SKEW by averaging daily SKEW over a week (Tuesday close to Tuesday close).

[3] There are several alternative ways to measure moneyness. For instance, Bollen and Whaley (2004) use Black-Scholes (1973) delta to measure moneyness, and Ni (2007) uses total volatility-adjusted strike-to-stock price ratio as one of the moneyness measures. We find quantitatively similar results using these alternative moneyness measures and present the main results with the simplest moneyness measure of strike price over stock price.

When there are multiple ATM and OTM options for one stock on one particular day, we further select options or weight all available options using different approaches to come up with one SKEW observation for each firm per day. Our main approach is based on the option's moneyness, which is also used in Ofek, Richardson, and Whitelaw (2004). That is, we choose one ATM call option with its moneyness closest to 1, and one OTM put option with its moneyness closest to 0.95. Alternatively, we compute a volume-weighted volatility skew measure, where we use option trading volumes as weights to compute the average implied volatilities for OTM puts and ATM calls for each stock each day. Obviously, if an option has zero volume during a particular day, the weight on this option will be zero. Thus, volume-weighted implied volatility only reflects information from options with non-zero volumes. We find that around 60% of firms have ATM call and OTM put options listed with valid price quotes and positive open interest, but these options are not traded everyday and thus have zero volumes from time to time. Compared to the volume-weighted SKEW, the moneyness-based SKEW utilizes all data available with valid closing quotes and positive open interests. Our later results mainly focus on the moneyness-based SKEW measure, but we always use the volume-weighted SKEW for a robustness check.[4]

We motivate the use of our SKEW measure from the demand-based option pricing model of Gârleanu, Pedersen, and Poteshman (2007). They find end-user's demand for index option is positively related to option expensiveness measured by implied volatility, which consequently affects the steepness of the implied volatility skew. Here we can develop similar intuition for individual stock volatility skew. If there is an overwhelming pessimistic perception of the stock, investors would tend to buy put options either for protection against future stock price drops (hedging purpose) or for a high potential return on the long put positions (speculative purpose). If there are more investors willing to long the put than those willing to short the put, both the price and the implied volatility of the put would increase,

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[4] We also consider several other alternative methods for computing SKEW when there are more than one pair of ATM calls and OTM puts, such as selecting the options with the highest volumes or open interests, or use open interests as weighting variables. Our results are not sensitive to which SKEW measure we choose to use. Results based on these alternative measures of SKEW are available upon request.

reflecting higher demand and leading to a steeper volatility skew. In general, high buying pressure for puts and steep volatility skew are associated with bad news about future stock prices. Empirically, we choose to use OTM puts to capture the severity of the bad news. When bad news is more severe, in terms of probability and/or magnitude, we expect stronger buying pressure on OTM puts and an increase in our SKEW variable. We choose to use implied volatility of ATM calls as the benchmark of implied volatility, because it is generally believed that ATM calls are one of the most liquid options traded and should reflect investors' consensus of the firm's uncertainty.[5] Due to data limitation, we do not directly calculate the buying pressure and selling pressure.

Table 1 provides summary statistics for the underlying stocks and options in our sample. We first calculate the summary statistics over the cross-section for each week, and then we average the statistics over the weekly time-series. We include firms with non-missing SKEW measures, where the SKEW measure is computed using implied volatilities of ATM calls with the strike-to-stock price ratio closest to 1 and OTM puts with the strike-to-stock price ratio closest to 0.95. We require all options to have positive open interests. The first two rows report firms' equity market capitalizations and book-to-market ratios. Naturally, firms in our sample are relatively large firms with low book-to-market ratios compared to those firms without traded options. Firms with listed options have an average market capitalization of $10.22 billion and a median of $2.45 billion, whereas firms without listed options have an average market capitalization of $0.63 billion and a median of $0.11 billion. To compute stock turnover, we divide the stock's monthly trading volume by the total number of shares outstanding. On average, 24% of shares are traded within a month. Thus, our sample firms are far more liquid than an average firm traded on NYSE/NASDAQ/AMEX, with a turnover of about 14% per month over the same period. The variable VOL^{STOCK} is the stock return volatility, calculated using daily return data over the past month. An average firm in this sample has an annualized volatility of around 47.14%, which is smaller than the average firm

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[5] ATM calls account for 25% of call and put options trading volumes combined in our sample. We do not use OTM calls because OTM calls are much less liquid, which account for less than 8% of total option trading volume.

level volatility of 57% for the sample of all stocks, as in Ang, Hodrick, Xing, and Zhang (2006). The reason, again, is that our sample is tilted toward large firms, and large firms tend to be relatively less volatile. The next three rows report summary statistics calculated from option data. VOL^{ATMC}, the implied volatility for an ATM call with the strike-to-stock price ratio closest to one, has an average of 47.95%, about 0.8% higher than the historical volatility, VOL^{STOCK}. This finding is consistent with Bakshi and Kapadia (2003a, 2003b), who argue that the difference between VOL^{ATMC} and VOL^{STOCK} is due to a negative volatility risk premium. VOL^{OTMP}, the implied volatility for an OTM put option with the strike-to-stock price ratio closest to 0.95, has an average of around 54.35%, much higher than both VOL^{STOCK} and VOL^{ATMC}. The variable SKEW*,* defined as the difference between VOL^{OTMP} and VOL^{ATMC}, has a mean of 6.40% and a median of 4.76%. Alternatively, when we compute SKEW using the option trading volume as the weighting variable, the mean and median of SKEW become 5.70% and 5.05%, respectively. The correlation between the moneyness-based SKEW and the volume-weighted SKEW is 80%.

[Insert Table 1 about here]

III. Can Volatility Skew Predict Future Stock Returns?

We argue that volatility skew reflects investors' expectation of a downward price jump. If informed traders choose the options market to trade in first and the stock market is slow to incorporate the information embedded in the options market, then we should see the information from the options market predicting future stock returns. In this section, we illustrate that option volatility skew predicts underlying equity returns using different methodologies. In subsection III.A, we conduct a Fama-MacBeth (1973) regression (FM regression hereafter) to examine whether volatility skew can predict the next week's returns, while controlling for different firm characteristics. In subsection III.B, we construct weekly long-short trading strategies based on the volatility skew measure. In subsection III.C, we examine time-series behavior of volatility skew, and whether predictability lasts beyond one week.

A. Fama-MacBeth Regression

The standard FM regression has two stages. In the first stage, we estimate the following regression in cross-section for each week t:

(2) $$\mathrm{RET}_{i,t} = b_{0t} + b_{1t}\mathrm{SKEW}_{i,t-1} + b_{2t}'\mathrm{CONTROLS}_{i,t-1} + e_{it},$$

where variable $\mathrm{RET}_{i,t}$ is firm i's return for week t (Wednesday close to Wednesday close) $\mathrm{SKEW}_{i,t-1}$ is firm i's volatility skew measure for week t-1 (Tuesday close to Tuesday close) and $\mathrm{CONTROLS}_{i,t-1}$ is a vector of control variables for firm i observed at week t-1. The options market closes at 4:02 p.m. for individual stock options, while the equity market closes at 4 p.m. If one uses same-day prices for both equity prices and option prices, as pointed out by Battalio and Schultz (2006), there exist serious non-synchronous trading issues. Therefore, we skip one day between weekly returns and weekly volatility skews to avoid non-synchronous trading issues. As one might expect, the results are even stronger if we do not skip one day.

After obtaining a time-series of slope coefficients, $\{b_{0t}, b_{1t}, b_{2t}\}$, the second stage of standard FM methodology is to conduct inference on the time-series of the coefficients by assuming the coefficients over time are i.i.d. For robustness, we also examine results when we allow the time-series of coefficients to have a trend or to have auto-correlation structures, by detrending or using the Newey-West (1987) adjustment. The results are close to those of the i.i.d. case and are available upon request. With the FM regression, not only can we easily examine the significance of the predictability of the SKEW variable, but we also can control for numerous firm characteristics at the same time.

We report the results for FM regression in Panel A of Table 2. In the first regression, we only include the volatility skew, and its coefficient estimate is -0.0061 with a statistically significant t-statistic of -2.50. To better understand the magnitude of the predictability, we compute the inter-quartile difference in next week's returns. From Table 1, the 25 percentile and 75 percentile of SKEW are 2.40% and 8.43%, respectively. When SKEW increases from 25 percentile to 75 percentile, the implied decrease in next week's return becomes (8.43%-2.40%) * (-0.0061) = - 5.52 basis points (or -2.90% per year).

[Insert Table 2 about here]

To separate the predictive power of volatility skew from other firm characteristics, we consider ten control variables in the second regression in Panel A of Table 2. The first six controls are from the equity market with potential predictive power in the cross-section of equity returns. The first control variable, SIZE, is firm equity market capitalization. Since Banz (1981), numerous papers have demonstrated that smaller firms have higher returns than larger firms. The second control variable, BM, is the book-to-market ratio, which is meant to capture the value premium (Fama and French 1993, 1996). The third control variable, LRET, is the past six-months of equity returns. We use this variable to control for possible momentum effect (Jegadeesh and Titman 1993) in stock returns. The fourth variable, VOL^{STOCK}, is stocks' historical volatilities, computed using one month of daily returns. The reason for including this variable is that Ang et al. (2006) show high historical volatility strongly predicts low subsequent returns. The fifth control variable, TURNOVER, is stock turnover. As in Lee and Swaminathan (2000) and Chordia and Swaminathan (2000), firm-level liquidity is strongly related to a firm's future stock return. The sixth characteristic variable, HSKEW, is the historical skewness measure for the stock, measured using one month of daily returns. Volatility skew is usually considered an indirect measure of skewness of the implied distribution under the risk-neutral probability, while historical skewness is computed under the real probability. The remaining four control variables are from the options market. The seventh control variable, PCR, the put-call ratio, is calculated as the average volume of puts over volume of calls from the last week. Pan and Poteshman (2006) show that high put-call ratio is related to low future stock returns.[6] The eighth control variable, PVOL, is the difference between the implied volatility of ATM call, VOL^{ATMC},

[6] Pan and Poteshman (2006) use newly initiated put-to-call ratio to predict equity returns. As newly initiated put-to-call ratio is not publicly available, our overall put-to-call ratio serves only as a rough approximation.

and historical stock return volatility, VOL^{STOCK}. We include this variable to examine whether the predictive power of SKEW is related to the negative volatility risk premium, as suggested by Bakshi and Kapadia (2003a, 2003b). Finally, we include option volumes on all contracts and option new open interests on all contracts to control for option trading activities.

Inclusion of the control variables does not reduce the predictive power of SKEW for the empirical results in Panel A of Table 2. Now the coefficient on volatility skew becomes -0.0089, with a *t*-statistic of -3.86. In terms of economic magnitude, the inter-quartile difference for future return becomes (8.43%-2.40%) * (-0.0089) = - 8.30 basis points (or -4.41% per year), where the inter-quartile numbers are reported in Table 1.

We now take a closer look at the coefficients on the control variables. The size variable carries a positive and insignificant coefficient, possibly because size effect is almost non-existent over our specific sample period from 1996 to 2005. It also may be due to the relatively large market capitalization of the firms in our sample. For the book-to-market variable, the coefficient is positive, which is consistent with the value effect, but it is not significant. The coefficient for lagged return over the past six months turns out to be positive and significant, indicating a strong momentum effect. The coefficients for the firm historical volatility and turnover are negative but insignificant. Surprisingly, the historical skewness is positive and significant. It is counterintuitive because previous work, such as Barbaris and Huang (2008), indicates one should expect higher return for more negatively skewed stocks. However, when we use historical skewness to predict n-week ahead returns, the pattern reverses (see section V.A.) The put-call ratio has a negative coefficient, which is consistent with the finding in Pan and Poteshman (2006), although insignificant. The coefficient on volatility premium, PVOL, is negative, indicating firms with higher volatility premiums have higher returns. However, the coefficient is insignificant. The coefficients on option volumes and option open interest are not significant.

We also provide results using volume-weighted volatility skew in Panel B of Table 2. The coefficient of volatility skew is statistically significant and larger in magnitude than the moneyness-based volatility skew measure. To summarize, after controlling for firm and option characteristics, the predictive power of SKEW remains economically large and statistically significant.

B. Long-Short Portfolio Trading Strategy

In this subsection, we demonstrate the predictability of SKEW using the portfolio sorting approach. Each week, we sort all sample firms into quintile portfolios based on the previous week average skew (Tuesday close to Tuesday close). Portfolio 1 includes firms with the lowest skews, and portfolio 5 includes firms with the highest skews. We then skip one day and compute the value-weighted quintile portfolio returns for the next week (Wednesday close to Wednesday close). If we long portfolio 1 and short portfolio 5, then the return on this long-short investment strategy heuristically illustrates the economic significance of the sorting SKEW variable. Compared to the linear regressions as in the FM approach, the portfolio sorting procedure has the advantage of not imposing a restrictive linear relation between the variable of interest and the return. Furthermore, by grouping individual firms into portfolios, we can reduce firm level noise in the data.

In Panel A of Table 3, we present the weekly quintile portfolio excess returns and characteristics based on the moneyness-based volatility skew measure. Each quintile portfolio has 168 stocks on average. Portfolio 1, containing firms with the lowest skews, has a weekly return in excess of the risk-free rate of 24 basis points (an annualized excess return of 13.18%), and portfolio 5, containing firms with the highest skews, has a weekly excess return of 8 basis points (an annualized excess return of 3.99%). Portfolio 5 underperforms portfolio 1 by 16 basis points per week (9.19% per year) with a *t*-statistic of -2.19, consistent with our conjecture that steeper volatility smirks forecast worse news. We adjust for risk by applying the Fama and French (1996) three-factor model. The Fama-French alphas for portfolios 1 and 5 are 10 basis points and -11 basis points per week, respectively. If we long portfolio 1 and short portfolio 5, the Fama-French alpha of the long-short strategy is 21 basis points per week (10.90% annualized) with a *t*-statistic of 2.93. It is evident that the large spread for this long-short strategy is driven by both portfolio 1 and portfolio 5.[7] From results not reported, if we conduct risk-adjustment by including market aggregate volatility risk, as in Ang, Hodrick, Xing, and Zhang (2006), the return spread is very similar to those when we use the Fama-French three-factor model. This suggests that the return spread between the low skew firms and high skew firms is not driven by their exposure to aggregate volatility risk.

[Insert Table 3 about here]

We also report several characteristics of the quintile portfolio firms in Panel A. The SIZE column exhibits a hump-shaped pattern from portfolio 1 to 5. Even though the market capitalizations for portfolio 1 and 5 are relatively smaller than those of the intermediate portfolios, their absolute magnitudes are still large, since our sample consists mainly of large cap firms. For the book-to-market ratio column, the pattern is relatively flat, except for the last quintile, where BM is higher than those of the other four quintiles. Stock return volatility, VOL^{STOCK}, displays a slightly downward trend from quintile 1 to quintile 5. The next column, PVOL, reports volatility premium. Interestingly, as SKEW increases from portfolio 1 to 5, PVOL decreases. Hence, for firms with low volatility skews, the options market prices the options higher than historical volatilities mandate, while high skew firms' options are less expensive than historical volatilities imply. It is possible that SKEW's predictive power is related to the magnitude of PVOL, yet our earlier FM regression results show PVOL doesn't have strong predictive power in a linear regression. In the last two columns, we report average volumes and average open interests for all contracts. It is interesting to see that volumes on firms with the lowest volatility skews are much higher than volumes on firms with the highest skews. However, high trading intensity is not a necessary condition for option prices to contain information. The open interest variable displays a similar pattern in the last column.[8]

[7] In our sample, 9.91% of observations have negative volatility skews. We also separate firms with positive skews and negative skews, and redo the portfolios sorting for firms with positive skews only. The return difference is very similar.

[8] From results not reported, we conduct a double sort based on volume/open interest and volatility skew. Our goal is to see whether the long-short strategy works better for firms with more option trading (in terms of higher

Panel B reports the returns and characteristics for quintile portfolios sorted on volume-weighted volatility skew, where options with zero volumes are implicitly excluded. By requiring positive trading volume, we impose a stricter requirement on option liquidity. As a consequence, sample size in Panel B is considerably smaller than in Panel A. Quintile portfolios in Panel B, on average, have 68 firms per week. By comparing Panels A and B, we find that firms with positive daily option volumes are twice as large in terms of market capitalization, and their SKEW measures are smaller. If we long the quintile portfolio with the lowest volume-weighted skew firms and short the quintile portfolio with the highest volume-weighted skew firms, the Fama-French adjusted return now becomes 19 basis points per week, or 10.06% annualized, with a *t*-statistic of 2.07. The patterns of characteristics in Panel B are qualitatively similar to those in Panel A with the exceptions on volume and open interest. With volume-weighted implied volatility, the volume and open interest are fairly flat across the quintile portfolios.

To summarize, we find firms with high volatility skews underperform firms with low volatility skews. The return difference is economically large and statistically significant, no matter which SKEW measure is used. In the interest of being concise, we only report results on moneyness-based SKEW for the remainder of the paper. Our results are quantitatively and qualitatively similar among different SKEW measures and are available upon request.

C. How Long Does the Predictability Last?

We have just shown that stocks with high volatility skews underperform those with low volatility skews in the subsequent week. In this subsection, we examine whether this underperformance lasts over longer horizons. If the stock market is very efficient in incorporating new information from the options market, the predictability would be temporary and unlikely to persist over a long period. Whether the predictability lasts over a

volume and larger open interest), and the results indicate that is the case.

longer horizon also might relate to the nature of the information. If the information is a temporary fad and has nothing to do with fundamentals, the predictability also would fade rather quickly. Of course, the definitions of “temporary” and “longer period” are relative. In this subsection, “temporary” refers to less than one week, and “longer period” refers to more than one week, but less than half a year. We take two approaches to investigate this issue: First, we examine whether volatility skew can predict future return after *n* weeks by using FM regressions; second, we examine portfolio holding period returns over different longer periods by using volatility skew from the previous week as the sorting variable.

Panel A of Table 4 reports the FM regression results. We focus on weekly returns from the 4th week (return over week t+4), the 8th week (return over week t+8) up until the 24th week (return over week t+24). We control for firm characteristics as well as option characteristics in all regressions, as in equation (2). We choose the dependent variables to be weekly returns, rather than cumulative returns such as from week t+1 to week t+4, because this allows us to easily compare magnitudes of parameters on the SKEW variable with the benchmark case of the next week (week t+1), as presented in the first two rows. The coefficients on volatility skew are significant for returns in the 4th week up to the 24th week. The coefficient on SKEW changes from -0.0089 in the first week to -0.0038 for the 24th week, indicating that the predictability weakens as the time horizon lengthens. Interestingly, historical skewness (HSKEW) now has the expected negative coefficients for all estimated horizons, and the coefficients are significant from the 4th week to the 16th week. Clearly, a positive and significant coefficient on historical skewness is only true for a one-week horizon. Over the longer term, a high historical skewness leads to negative returns, which is consistent with explanations based on investor preferences for skewed assets, as in Barbaris and Huang (2008).

[Insert Table 4 about here]

Table 4 Panel B presents portfolio holding period returns results. First, we sort firms into quintile portfolios based on last week’s volatility skew measure, and then we compute the value-weighted holding period returns for the next 4 weeks (from week t+1 to week t+4), the next 8 weeks (from week t+1 to week t+8) and up until week 28 (from week t+1 to week t+28). Different from Panel A, here we present cumulative holding period returns, rather than weekly returns, because it is easier for portfolio managers to understand the magnitudes for different holding periods. These holding period returns are annualized and are adjusted by the Fama-French three-factor model. The t-statistics are adjusted using Newey-West (1987), because the holding period returns overlap. For a holding period of one week, as in Table 3, the alpha difference between firms with the lowest skews and the highest skews is 10.90%. The alpha difference drops to 6.52% when we extend the holding period to 4 weeks. This is almost 40% smaller than the alpha if we hold the portfolio for one week. For holding period returns from 8 to 28 weeks, the risk-adjusted returns for the long-short strategy stay between 6% and 7%. It declines further after week 28. The results suggest that the stock market is slow in incorporating information embedded in option prices. The predictability of volatility skew lasts over the 28-week horizon and then slowly dies out.

We conduct additional analysis on volatility skew to investigate whether volatility skew itself is persistent or mean-reverting. First, we calculate the auto-correlation coefficient of the volatility skew measure. In Panel C of Table 4, the first order auto-correlation coefficient is 66%, and then the autocorrelation goes down almost monotonically to around 20% for the 8th order auto-correlation. This indicates that volatility skew is not highly persistent over weekly horizon.

Figure 1 plots the evolution of the average volatility skew for firms belonging to different quintile portfolios sorted on week 0's volatility skew. It spans 24 weeks before and after the portfolio formation time, which is week 0. The figure clearly shows that for the firms with the highest volatility skews at week 0, average volatility skew starts to increase about 2-3 weeks before portfolio formation, and it quickly decreases over week +1 to +3 after it reaches the peak at week 0. Afterwards the speed of decreasing slows down. The pattern for firms with the lowest volatility skews is the opposite. Overall, the figure indicates that the big increase in volatility skew for portfolio 1 firms is short-term, as driven by short-term information, rather than permanent.

[Insert Figure 1 about here]

To summarize, the results in this subsection show that the predictability of volatility skew lasts for as long as around a half year, suggesting the equity market is slow in reacting to information in the options market.

IV. Volatility Smirks and Future Earnings Surprises

Given the strong predictability of volatility skew, the next natural question becomes: What is the nature of the information embedded in volatility skew? Broadly speaking, information relevant for a firm's stock price includes news to its discount rate and news to its future cash flows. The news could be at the aggregate market level, at the industry level, or it could be firm-specific. Since the volatility skew is a firm-specific variable, we focus on firm-level information rather than on aggregate information. Nevertheless, we do not rule out the possibility that there are some underlying macroeconomic factors which affect the volatility skew in a systematic fashion, and we leave that to potential future studies.

The most important firm-level event is a firm's earnings announcement. Dubinsky and Johannes (2006) note that most of the volatility in stock returns is concentrated around earnings announcement days. This indicates that a firm's earnings announcement is a major channel for new information release. Hence, in this section we investigate whether the option volatility skew contains information related to future earnings.[9]

First, we sort firms into quintile portfolios based on the volatility skew. Then, we examine the next quarterly earnings surprise for firms in each quintile portfolio. The earnings surprise variable, UE, is the difference between announced earnings and the latest consensus

[9] In a related paper, Amin and Lee (1997) examine trading activities in the four-day period just before earnings announcements and document that option trading volume is related to price discovery of earnings news.

earnings forecast before the announcement. We also scale the earnings surprise variable, UE, by the standard deviation of the latest consensus earnings forecast, and this gives us the standardized earnings surprise variable SUE. If the information in SKEW is related to news about firms' earnings, firms with the highest skews are likely to be firms with the worst news, and they should have the lowest UE/SUE in the next quarter. Since our sample firms are generally large firms, about 80% of these firms have earnings forecast data available within the next 12-week interval. So the results in this section are representative of the general cross section in this article.

We report earnings surprise statistics in Table 5. Panel A includes all observations with an earnings release within the next n weeks after observing the volatility skew variable, where n = 4, 8, 12, 16, 20, and 24. Consider n = 12 as an example: The difference in UE between the lowest 20% of firms ranked by volatility skew and the highest 20% of firms is 0.63 of a cent ($.0063), with a significant t-statistic of 3.04. Given the average size of UE to be 2 cents, the 0.63 of a cent difference is economically significant. The results on SUE are qualitatively similar. The above findings are consistent with the hypothesis that SKEW is related to future earnings, and higher SKEW suggests worse news.

[Insert Table 5 about here]

We also conduct FM regression to investigate whether volatility skew can predict future earnings surprise. To be more specific, we examine whether the coefficient on volatility skew is significantly negative for earnings announcement within the next n-weeks, where n = 4, 8, 12, 16, 18, 20, and 24. The results are presented in Panel B of Table 5. In the left, we use volatility skew to predict future UE, and we predict SUE in the right. For the UE regressions, the coefficient estimates for the volatility skew range between -0.033 to -0.045 and are statistically significant over all the horizons from week 4 to 24. The results on SUE are qualitatively similar.

The results demonstrate a close link between the shape of the volatility smirk and future news about firm fundamentals. We find firms with the highest skews are firms with the worst earnings surprise in the near future between 1 and 6 months. This empirical finding is suggestive of the superior informational advantage option traders have over stock traders.

V. Discussion on Related Literature

A. Volatility Skew vs. Risk Neutral Skew

A few papers, such as Conrad, Dittmar, and Ghysels (2007) and Zhang (2005), indicate that lower skewness leads to higher return. The intuition is that firms with more negative skewness are riskier and thus should receive higher expected returns as compensation. However, the skewness measures used in these studies are either risk neutral skewness or historical skewness, under the assumption that there is no arbitrage or information difference between options market and stock market.

Bakshi, Kapadia, and Madan (2003) show that more negative risk neutral skewness equals a steeper slope of implied volatilities, everything else being equal. Thus, our volatility skew measure is negatively related to risk neutral skewness. In previous sections, we show that firms with higher volatility skews have lower average returns. If our volatility skew is a proxy for risk neutral skewness or historical skewness, then our finding is at odds with the risk explanations mentioned above. In this subsection, we empirically separate the predictive power of volatility skew, risk neutral skewness, and historical skewness.

We compute risk neutral skewness, denoted by RNSKEW, following Bakshi, Kapadia, and Madan's (2003, BKM hereafter) procedure. BKM show that higher moments in the risk neutral world, such as skewness and kurtosis, can be expressed as functions of OTM calls and OTM puts. Based on equation (5) – equation (9) in BKM, we compute the risk neutral skewness using at least two pairs of OTM calls and OTM puts for each day. Next, we average the daily risk neutral skewness over a week to obtain weekly measures that are compatible in frequency with the volatility skew measure. Since not all stocks have more than two pairs of

OTM calls and OTM puts each day, we only require a stock to have more than two daily observations in each week to be included in our weekly sample. Even so, many smaller stocks don't have two pairs of OTM calls and OTM puts with valid price quotes. Finally, there are only about 140 firms with weekly risk neutral skewness for each week, on average, which is substantially smaller than the sample size with the volatility skew measure available. Due to the significant smaller sample size, results in this subsection should be interpreted with caution.

We first investigate the correlations between different skewness measures. As expected, the cross-sectional correlation between volatility skew and risk neutral skewness is -29%. Historical skewness has close to zero correlations with the other two skewness measures: Its correlation with volatility skew is 1.79%, and its correlation with risk neutral skewness is -0.43%.

To separate the explanatory power of volatility skew, risk neutral skewness, and historical skewness, we apply an FM regression, rather than double sorting, due to the limited number of firms with available risk neutral skewness data. In the FM regression, we use all three skewness measures to predict the weekly return in the first, 4^{th} through 24^{th} week after the skewness measures are observed. Using the regression, we test two hypotheses: first, whether volatility skew can still predict future stock returns in the presence of other skewness measures; second, whether the risk neutral skewness and historical skewness can predict future stock returns, and whether they carry a negative sign as expected from a risk explanation.

Table 6 reports the regression results. In the left panel, we do not include characteristics variables as controls, and in the right panel we include the 10 control variables as in equation (2). For the sample of firms with risk neutral skewness available, the volatility skew is negative and statistically significant in predicting next week's returns when there are no control variables. However, the predictability weakens substantially when we extend the weekly returns further into the future. The risk neutral skewness measure does not appear to be significant in any regression. Historical skewness has an expected negative coefficient over horizons longer than one week. The results suggest that risk neutral skewness and volatility skew contain different information for future equity returns. Bakshi, Kapadia, and Madan (2003) show that implied volatility can be expressed as a linear transformation of risk neutral higher moments like skewness and kurtosis. The correlation between risk neutral skewness and volatility skew in our sample is fairly low at -29%. It is possible that, in addition to risk neutral skewness, there are additional factors, such as risk neutral kurtosis, that affect the shape of the volatility skew. This may lead to the difference in predictive power of SKEW and RNSKEW.

[Insert Table 6 about here]

Overall, the volatility skew and historical skewness both have weak predictive power in the presence of risk neutral skewness for a much smaller sample size. Risk neutral skewness doesn't predict future returns. It is likely that volatility skew and risk neutral skewness contain different information, and this might explain the differences between our findings and those of Conrad, Dittmar, and Ghysels (2007).

B. Where Do Informed Traders Trade?

We have documented that the volatility skew variable can predict the underlying cross-sectional equity returns, and we argue that the informational advantage of some option traders might be the reason for the observed predictability. In this subsection, we investigate the question of when informed traders would choose to trade in options market rather than equity market.

Easley, O'Hara, and Srinivas (1998) provide a theoretical framework for understanding where informed traders trade. In the pooling equilibrium of their model, given access to both the stock market and the options market, profit-maximizing informed traders may choose to trade in one or both markets. Informed traders would choose to trade in the options market if the options traded provide high leverage, and/or if there are many informed traders in the stock market, and/or the stock market for the particular firm is illiquid. Presumably, the predictive power of volatility skew would be stronger when more informed traders choose to trade in the options market. To test the above conjecture, we first define measurable proxies for the key variables. For option leverage, we use option's delta, which is the first-order derivative of option price with respect to stock price. Since informed traders are more likely to use OTM puts to trade and reveal severe negative information, we use the deltas of OTM puts, rather than the deltas of ATM calls. The higher leverage of a put option is equivalent to a more negative delta. We follow Easley, Hvidkjaer, and O'Hara (2002) to use the PIN[10] measure, i.e., probability of informed trading, to proxy for the percentage of informed trading for individual stocks. Finally, we use stock turnover to proxy for the stock trading liquidity.

To investigate how the SKEW's predictability changes with the option's delta, PIN, and stock turnover, we estimate another set of Fama-MacBeth regressions by adding in interaction terms:

$$
\begin{aligned}
&\mathrm{RET}_{i,t} = b_{0t} + (b_{1t} + c_{1t}\mathrm{TURNOVER}_{i,t-1})\mathrm{SKEW}_{i,t-1} + b_{2t}\mathrm{CONTROLS}_{i,t-1} + e_{it}, \\
(3)\qquad &\mathrm{RET}_{i,t} = b_{0t} + (b_{1t} + c_{2t}\mathrm{DELTA}_{i,t-1})\mathrm{SKEW}_{i,t-1} + b_{2t}\mathrm{CONTROLS}_{i,t-1} + e_{it}, \\
&\mathrm{RET}_{i,t} = b_{0t} + (b_{1t} + c_{3t}\mathrm{PIN}_{i,t-1})\mathrm{SKEW}_{i,t-1} + b_{2t}\mathrm{CONTROLS}_{i,t-1} + e_{it}.
\end{aligned}
$$

To be consistent with Easley et al. (1998), the predictability of SKEW should be increasing in stock market illiquidity, option delta, and stock market asymmetric information. Thus, the coefficient c_1 should be negative, the coefficient c_2 should be positive and the coefficient c_3 should be negative.

Table 7 presents the Fama-MacBeth regression results. In the first regression, the interaction between SKEW and TURNOVER carries a negative sign, which indicates that when stock market liquidity deteriorates, the predictive power of SKEW becomes stronger. In the second regression, we find the coefficient on the interaction between SKEW and OTM put delta has a positive sign and is marginally significant. This implies that when OTM put

[10] The data on PIN is obtained from Soeren Hvidkjaer's Web site for the sample period from 1996-2002. So the regression with PIN would have a shorter sample period than other regressions.

option deltas become more negative, i.e., options become more leveraged, more informed traders prefer to choose options market to trade and cause stronger predictability of the volatility skew variable. Finally, the interaction between SKEW and PIN is positive, indicating that as information asymmetry increases in the stock market, the predictability of volatility skew becomes weaker. Apart from the PIN measure, the regression results are consistent with the model predictions in Easley et al. (1998). Although most of the coefficients are insignificant, the SKEW variable always has a negative sign.

[Insert Table 7 about here]

VI. Conclusion

Informed traders might choose to trade in different markets to benefit from their informational advantage. Thus, one market could lead another market in the price discovery process. In this paper we investigate whether the shape of the volatility smirk contains relevant information for the underlying stock's future returns. We define the volatility skew variable as the difference between the implied volatilities of out-of-the-money puts and at-the-money calls. Empirically, the majority of individual stock options exhibit a downward sloping volatility smirk pattern. We find that volatility skew has significant predictive power for future cross-sectional equity returns. Firms with the steepest volatility skews underperform those with the least pronounced volatility skews. This cross-sectional predictability is robust to various controls and is persistent for at least six months. The predictability we document is consistent with Gârleanu, Pedersen, and Poteshman's (2007) model that shows demand is positively related to option expensiveness. It also suggests that informed traders trade in the options market and that the stock market is slow to incorporate information from the options market. We further document that firms with the steepest volatility smirks are those experiencing the worst earnings shocks in subsequent months, suggesting that the information embedded in the shape of the volatility smirk is related to firm fundamentals.

Data Appendix

The option data are obtained from OptionMetrics. We apply the following filters to the daily option data:

1. The underlying stock's volume for that day is positive.
2. The underlying stock's price for that day is higher than $5.
3. The implied volatility of the option is between 3% and 200%.
4. The option's price (average of best bid price and best ask price) is higher than $0.125.
5. The option contract has positive open interest and non-missing volume data.
6. The option matures within 10 to 60 days.

For the at-the-money call options, we require the option's moneyness to be between 0.95 and 1.05. For the out of money put options, we require the option's moneyness to be between 0.80 and 0.95. We compute firm daily volatility skew by using the daily difference between implied volatilities of at-the-money calls and out-of-the-money puts. The daily skew dataset on average has 1,005 firms each day over the sample period 1996 – 2005.

We choose the ATM call as a benchmark for implied volatility because it has the highest liquidity among all traded options. In fact, in terms of volume, the average daily volume for ATM calls accounts for about 25% of volume for all call and put options combined. The ATM puts account for 17% of daily volume, and the OTM puts account for another 10%. On average, each firm has about two ATM call options each day, and we chose the one with moneyness closest to 1.00. Each firm has approximately one OTM put option daily.

When we construct the weekly volatility skew dataset, we only include firms that have at least two non-missing daily skew observations within the week. The weekly skew dataset on average has 840 firms each week over the sample period 1996 – 2005.

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Table 1: Summary Statistics

Data are obtained from CRSP and Compustat (for stocks) and OptionMetrics (for options). Our sample period is 1996 to 2005. Variable SIZE is the firm market capitalization in \$ billions. Variable BM is the book-to-market ratio. Variable TURNOVER is calculated as monthly volume divided by shares outstanding. Variable VOL^{STOCK} is the underlying stock return volatility, calculated using last month's daily stock returns. Variable VOL^{ATMC} is the implied volatility for at-the-money calls, with the strike-to-stock price closest to 1. Variable VOL^{OTMP} is the implied volatility for out-of-the-money puts, with the strike-to-stock price closest to 0.95. Variable SKEW is the difference between VOL^{OTMP} and VOL^{ATMC}. We first calculate the summary statistics over the cross-section for each week, then we average the statistics over the weekly time-series. For each week, there are on average 840 firms in the sample.

Variable	Mean	5%	25%	50%	75%	95%
SIZE	10.22	0.35	0.94	2.45	7.56	45.14
BM	0.40	0.07	0.17	0.30	0.50	0.99
TURNOVER (%)	0.24	0.05	0.09	0.16	0.29	0.68
VOL^{STOCK} (%)	47.14	19.78	29.41	41.37	58.87	92.83
VOL^{ATMC} (%)	47.95	24.00	32.91	44.53	60.03	82.84
VOL^{OTMP} (%)	54.35	29.07	38.93	51.25	66.65	89.87
SKEW (%)	6.40	-0.99	2.40	4.76	8.43	19.92

Table 2: Predictability of Volatility Skew after Controlling for Other Effects, Fama-MacBeth Regression

Data is obtained from CRSP and Compustat (for stocks) and OptionMetrics (for options). Our sample period is 1996 to 2005. Variable SKEW is the difference between the implied volatilities of out-of-the-money put options and at-the-money call options. Variable LOGSIZE is the logged firm market capitalization. Variable BM is the book-to-market ratio. Variable LRET is the last six-month return. Variable VOL^{STOCK} is the underlying return volatility calculated using last month's daily stock returns. Variable TURNOVER is the stock trade volume over number of shares outstanding. Variable HSKEW is the underlying return skewness calculated using last month's daily stock returns. Variable PCR is the option volume put-call ratio. Variable PVOL is the volatility premium, which is the difference between the implied volatility for at-the-money call options and VOL^{STOCK}. Variable VOLUME is the total volume on all option contracts. Variable OPEN is the total open interest on all option contracts. In both panels, we report Fama-MacBeth regression estimates for weekly returns, as specified in equation (2). In Panel A, the implied volatilities are the implied volatilities on ATM calls with moneyness closest to 1 and OTM puts with moneyness closest to 0.95. In Panel B, the implied volatilities are volume weighted for ATM calls and OTM puts. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A. Fama-MacBeth regression for one week return, using moneyness-based SKEW

		SKEW	LOGSIZE	BM	LRET	VOL^{STOCK}	TURNOVER	HSKEW	PCR	PVOL	VOLUME	OPEN	ADJ R2
I	coef.	-0.0061											0.18%
	t-stat	-2.50**											
II	coef.	-0.0089	0.0001	0.0006	0.0037	-0.0034	0.0000	0.0011	0.0000	-0.0008	0.0000	0.0000	8.52%
	t-stat	-3.86***	0.24	1.49	3.52***	-0.97	0.33	5.69***	-0.55	-0.25	-0.34	0.45	

Panel B. Fama-MacBeth regression for one week return, using volume-weighted SKEW

		SKEW	LOGSIZE	BM	LRET	VOL^{STOCK}	TURNOVER	HSKEW	PCR	PVOL	VOLUME	OPEN	ADJ R2
I	coef.	-0.0223											0.18%
	t-stat	-4.30***											
II	coef.	-0.0216	0.0003	0.0015	0.0032	-0.0038	0.0000	0.0011	-0.0001	0.0008	0.0000	0.0000	11.11%
	t-stat	-4.09***	0.89	1.79*	2.73***	-0.93	0.20	3.62***	-0.81	0.20	-0.12	-0.29	

Table 3: Predictability of Volatility Skew, Portfolio Forming Approach

Data is obtained from CRSP and Compustat (for stocks) and OptionMetrics (for options). Our sample period is 1996 to 2005. Variable SKEW is the difference between the implied volatilities of out-of-the-money put options and at-the-money call options. Variable EXRET is the weekly excess return over risk-free rate. Variable ALPHA is the weekly risk-adjusted return using the Fama-French 3-factor model. Variable SIZE is the firm market capitalization in $ billions. Variable BM is the book-to-market ratio. Variable VOL^{STOCK} is the underlying return volatility calculated using last month's daily stock returns. Variable PVOL is the volatility premium, which is the difference between the implied volatility for at-the-money call options and VOL^{STOCK}. Variable VOLUME is the total volume on all option contracts. Variable OPEN is the total open interest on all option contracts. Both panels report summary statistics for quintile portfolios sorted on the last week's SKEW. For each week, we form quintile portfolios based on the average skew from last week. We then skip a day and hold the quintile portfolios for another week. In Panel A, the implied volatilities are the implied volatilities on ATM calls with moneyness closest to 1 and OTM puts with moneyness closest to 0.95. On average, each quintile portfolio contains 168 firms. In Panel B, the implied volatilities are volume weighted for ATM calls and OTM puts. On average, each quintile portfolio contains 68 firms. The *t*-statistics for mean returns and alphas are calculated over 520 weeks. The firm characteristics are computed by averaging over the firms within each quintile portfolio and then over 520 weeks. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A. Quintile portfolios, using moneyness-based SKEW

	EX RET	ALPHA	SKEW	SIZE	BM	VOL^{STOCK}	PVOL	VOLUME	OPEN
low	0.24%	0.10%	-0.34%	7.82	0.394	0.504	3.03%	1042	10718
2	0.15%	0.03%	2.87%	13.81	0.377	0.454	1.11%	1234	13890
3	0.16%	0.03%	4.79%	14.70	0.373	0.459	0.51%	1258	14299
4	0.11%	-0.02%	7.55%	10.46	0.398	0.474	0.18%	962	10865
high	0.08%	-0.11%	17.14%	4.29	0.468	0.466	-0.80%	469	5618
low-high	0.16%	0.21%							
t-stat	2.19**	2.93***							

Panel B. Quintile portfolios, using volume-based SKEW

	EX RET	ALPHA	SKEW	SIZE	BM	VOL^{STOCK}	PVOL	VOLUME	OPEN
low	0.26%	0.14%	0.48%	13.56	0.342	0.543	1.98%	1994	18222
2	0.21%	0.08%	3.45%	22.25	0.316	0.483	0.21%	2244	22987
3	0.14%	0.04%	5.06%	25.57	0.301	0.487	-0.56%	2525	26839
4	0.15%	0.04%	6.96%	23.95	0.302	0.506	-0.96%	2535	26918
high	0.07%	-0.05%	12.54%	13.26	0.348	0.558	-1.27%	2024	21859
low-high	0.19%	0.19%							
t-stat	2.05**	2.07**							

Table 4: How Long Does SKEW's Predictability Last?

Data is obtained from CRSP and Compustat (for stocks) and OptionMetrics (for options). Our sample period is 1996 to 2005. Variable SKEW is the difference between the implied volatilities of out-of-the-money put options (strike/stock closest to 0.95) and at-the-money call options (strike/stock closest to 1). Variable LOGSIZE is the logged firm market capitalization. Variable BM is the book-to-market ratio. Variable LRET is the last six-month return. Variable VOL^{STOCK} is the underlying return volatility calculated using last month's daily stock returns. Variable TURNOVER is the stock trade volume over number of shares outstanding. Variable HSKEW is the underlying return skewness calculated using last month's daily stock returns. Variable PCR is the option volume put-call ratio. Variable PVOL is the volatility premium, which is the difference between the implied volatility for at-the-money call options and VOL^{STOCK}. Variable VOLUME is the total volume on all option contracts. Variable OPEN is the total open interest on all option contracts. In Panel A, we report Fama-MacBeth regression estimates for n-week ahead weekly returns, with n = 1, 4, 8, ..., 24. Panel B reports cumulative holding period returns for quintile portfolios sorted on the last week's skew over the next n weeks, with n = 4, 8, ..., 28. All returns are adjusted by the Fama-French 3-factor model, and the risk-adjusted returns are annualized. Panel C reports autocorrelation coefficients of the SKEW. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A. Predict future *n*-th weekly returns, Fama-MacBeth regression

n-th week		SKEW	LOGSIZE	BM	LRET	VOL^{STOCK}	TURNOVER	HSKEW	PCR	PVOL	VOLUME	OPEN	ADJ R2
1	coef.	-0.0216	0.0003	0.0015	0.0032	-0.0038	0.0000	0.0008	0.0011	-0.0001	0.0000	0.0000	11.11%
	t-stat	-4.09***	0.89	1.79*	2.73***	-0.93	0.20	0.20	3.62***	-0.81	-0.12	-0.29	
4	coef.	-0.0067	-0.0002	0.0008	0.0016	-0.0037	0.0001	-0.0004	0.0000	-0.0027	0.0000	0.0000	7.88%
	t-stat	-3.27***	-1.07	1.97**	1.67*	-1.08	0.81	-2.30**	-0.02	-0.88	-0.60	0.76	
8	coef.	-0.0040	-0.0005	0.0002	0.0016	-0.0055	0.0001	-0.0003	0.0000	-0.0044	0.0000	0.0000	7.80%
	t-stat	-1.89	-2.04**	0.49	1.64	-1.58	1.21	-1.93*	1.81*	-1.42	0.60	0.74	
12	coef.	-0.0026	-0.0003	0.0005	0.0015	-0.0038	0.0001	-0.0004	0.0000	-0.0050	0.0000	0.0000	7.44%
	t-stat	-1.30	-1.52	1.15	1.64	-1.09	0.60	-2.21**	0.13	-1.55	1.41	-0.33	
16	coef.	-0.0052	-0.0003	0.0011	0.0021	-0.0011	0.0000	-0.0005	0.0000	-0.0002	0.0000	0.0000	7.30%
	t-stat	-2.47**	-1.25	2.43**	2.24**	-0.32	-0.14	-2.97***	-0.70	-0.07	1.37	0.03	
20	coef.	-0.0043	-0.0003	0.0006	0.0020	-0.0033	0.0000	-0.0001	0.0000	-0.0049	0.0000	0.0000	7.14%
	t-stat	-2.03**	-1.29	1.38	2.24**	-0.93	0.35	-0.43	1.37	-1.52	0.35	0.69	

24	coef.	-0.0038	-0.0005	0.0008	0.0019	-0.0030	0.0000	-0.0003	0.0000	-0.0034	0.0000	0.0000	6.77%
	t-stat	-1.82	-2.41**	1.90*	2.21**	-0.86	-0.17	-1.52	-0.56	-1.04	0.05	1.51	

Panel B. Holding period returns for the next *n* weeks, risk adjusted by the Fama-French 3-factor model

n weeks	4	8	12	16	20	24	28
low	3.40%	3.55%	3.97%	3.46%	3.59%	3.94%	3.51%
2	1.15%	1.84%	2.28%	2.43%	2.35%	2.43%	1.98%
3	1.69%	0.90%	0.76%	0.87%	0.89%	0.97%	1.20%
4	-1.33%	-0.58%	-1.12%	-1.25%	-0.77%	-0.72%	-0.68%
high	-3.12%	-3.32%	-3.16%	-2.53%	-2.92%	-3.11%	-2.87%
low-high	6.52%	6.88%	7.14%	5.99%	6.50%	7.04%	6.38%
t-stat	2.70***	3.73***	4.23***	4.32***	4.34***	4.33***	4.31***

Panel C. Auto correlations for SKEW

AR1	AR2	AR3	AR4	AR5	AR6	AR7	AR8
0.660	0.412	0.316	0.285	0.251	0.195	0.189	0.225

Table 5: Option Volatility Smirks and Future Earnings Surprises

Data is obtained from CRSP and IBES (for stocks) and OptionMetrics (for options). Our sample period is 1996 to 2005. Variable SKEW is the difference between the implied volatilities of out-of-the-money put options (strike/stock closest to 0.95) and the at-the-money call options (strike/stock closest to 1). Variable UE is the unexpected earnings, the difference between announced earnings and the latest earnings forecast consensus. Variable SUE is the standardized UE, where UE is divided by volatility of analyst forecasts. In Panel A, we sort stocks into quintiles based on last week's average SKEW. We then check the average future UE/SUE for each portfolio, where the firms have an earnings release within the next n-weeks, with n = 4, 8, ..., 24. In Panel B, we use Fama-MacBeth regression to investigate whether last week's volatility skew is able to predict future UE/SUE within the next n-weeks, with n = 4, 8, ..., 24. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A. Earnings surprises for firms with earnings announcements within the next *n* weeks

	UE		SUE	
n weeks	low SKEW – high SKEW	*t*-stat	low SKEW – high SKEW	*t*-stat
4	0.0087	3.24***	0.3167	2.63***
8	0.0088	2.59***	0.3163	3.01***
12	0.0063	3.04***	0.3369	2.88***
16	0.0062	2.35**	0.3427	2.43**
20	0.0104	3.85***	0.4881	4.40***
24	0.0074	2.62**	0.3672	2.10**

Panel B. Predicting future earnings surprise within next *n* weeks using last week's SKEW, Fama-MacBeth regression

	UE		SUE	
n weeks	coef.	*t*-stat	coef.	*t*-stat
4	-0.039	-2.51**	-1.847	-2.98***
8	-0.045	-2.78***	-2.023	-3.57***
12	-0.033	-3.26***	-2.063	-3.72***
16	-0.033	-2.98***	-1.980	-2.75***
20	-0.053	-3.43***	-2.681	-3.66***
24	-0.041	-2.87***	-2.188	-2.61***

Table 6: Distinguishing Between Different Skew Measures, Fama-MacBeth Regression

Data is obtained from CRSP and Compustat (for stocks) and OptionMetrics (for options). Our sample period is 1996 to 2005. Variable SKEW is the difference between the implied volatilities of out-of-the-money put options (strike/stock closest to 0.95) and at-the-money call options (strike/stock closest to 1). Variable RNSKEW is the risk neutral skewness estimated following Bakshi, Kapadia, and Madan (2003). Variable HSKEW is the historical skewness estimated using the last month's daily return. We report the Fama-MacBeth regression estimates for n-week ahead weekly returns, where n = 1, 4, ..., 24. The control variables are the same as in equation (2). Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

		Without Controls			With Controls		
n-th week		SKEW	RNSKEW	HSKEW	SKEW	RNSKEW	HSKEW
1	coef.	-0.0457	0.0014	0.0021	-0.0324	0.0001	0.0017
	t-stat	-2.67***	0.76	3.93***	-1.74*	0.07	2.63***
4	coef.	0.0022	0.0004	-0.0001	-0.0121	-0.0002	-0.0003
	t-stat	0.15	0.24	-0.21	-0.64	-0.11	-0.66
8	coef.	-0.0172	-0.0006	-0.0002	0.0285	0.0049	-0.0008
	t-stat	-1.23	-0.37	-0.48	0.86	1.23	-1.11
12	coef.	-0.0008	0.0021	-0.0010	-0.0444	-0.0023	-0.0003
	t-stat	-0.05	1.24	-2.10**	-0.82	-0.35	-0.30
16	coef.	0.0006	0.0027	-0.0005	0.0252	0.0070	-0.0010
	t-stat	0.04	1.42	-1.10	0.75	1.62	-1.55
20	coef.	0.0073	0.0009	-0.0013	0.0586	0.0075	-0.0023
	t-stat	0.52	0.56	-2.56**	1.35	1.30	-2.24**
24	coef.	-0.0154	0.0007	-0.0005	-0.0354	0.0011	0.0004
	t-stat	-1.12	0.39	-1.18	-1.44	0.52	0.44

Table 7: Where Do Informed Traders Trade?

Data is obtained from CRSP and Compustat (for stocks) and OptionMetrics (for options). Our sample period is 1996 to 2005. Variable SKEW is the difference between the implied volatilities of out-of-the-money put options (strike/stock closest to 0.95) and at-the-money call options (strike/stock closest to 1). Variable TURNOVER is the stock trade volume over the number of shares outstanding. Variable DELTA is the delta of the OTM put option. Variable PIN is the PIN measure from Easley, O'Hara, and Hvidkjaer (2002). We report Fama-MacBeth regression results as specified in equation (3). Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

		SKEW	SKEW* TURNOVER	SKEW* DELTA	SKEW* PIN	adj R2
I	coef.	-0.0050	-0.0015			8.08%
	t-stat	-1.73*	-1.38			
II	coef.	-0.0028		0.0407		7.82%
	t-stat	-0.67		1.49		
III	coef.	-0.0088			0.0385	7.46%
	t-stat	-1.07			0.65	

Figure 1: Evolution of Volatility Skew Over [-24, +24]

Data is obtained from CRSP and Compustat (for stocks) and OptionMetrics (for options). Our sample period is 1996 to 2005. Variable SKEW is the difference between the implied volatilities of out-of-the-money put options (strike/stock closest to 0.95) and at-the-money call options (strike/stock closest to 1). In the figure, we track the average volatility skew for firms within quintile portfolios between 24 weeks before the sorting and 24 weeks after the sorting, while the ranks of quintile portfolios are determined based on SKEW at week 0.