ESSAYS ON THE INFORMATION FLOW FROM OPTION MARKETS TO STOCK MARKETS

by

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A dissertation submitted to the Graduate Faculty in Business in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

The City University of New York

2010

This manuscript has been read and accepted for the Graduate Faculty in Business in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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ABSTRACT

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Informed traders might prefer the option markets over stock markets due to advantages offered by option trading such as reduced transaction costs, enhanced opportunities for taking short positions and higher leverage. The first chapter of this dissertation provides a brief review of the empirical and theoretical literatures related to this question.

The second chapter investigates the intertemporal relation between volatility spreads and expected market returns. If informed traders who prefer to trade in the option markets demand more put (call) options before negative (positive) price movements due to their private information, then one would expect to see a significantly negative intertemporal relation between put minus call implied volatility spreads and aggregate returns. The results indicate that volatility spreads are significantly and negatively related to expected market returns after controlling for conditional variance and macroeconomic variables that proxy for the changes in future investment opportunities. Since the volatility spreads may also proxy for skewness, direct physical and risk-neutral skewness measures are constructed and the results indicate that there is no significant relation between various measures of skewness and expected market returns. The predictive ability of volatility spreads is stronger when consumer sentiment index is unusually high or low.

The third chapter brings a more thorough look into the predictive ability of deviations from put-call parity on stock returns. If the trading activity of informed investors is an important driver of deviations from put-call parity, then the predictability of stock returns should be more pronounced during major information events such as earnings announcements. These deviations are measured by the implied volatility spreads between pairs of matched put and call options. During a two-day earnings announcement window, the abnormal returns to a portfolio that buys stocks with relatively expensive call options is about 2 percent greater than the abnormal returns to a portfolio that buys stocks with relatively expensive put options. The informational role of option markets is further supported by the findings that the degree of announcement return predictability is stronger when deviations from put-call parity are measured using more liquid options, information environment is more asymmetric and stock liquidity is low.

ACKNOWLEDGEMENTS

The completion of this dissertation was made possible by many individuals. First of all, I would like to thank my parents, Ertuğrul and Nurhayat, for their unconditional love and support. I would like to dedicate this dissertation to my cousin Volkan whose presence is sorely missed.

I owe special gratitude to my advisors, Professor Turan G. Bali and Professor K. Özgür Demirtaş, who tirelessly and patiently gave me advice and guided me throughout my doctoral studies. Without their support, belief and willingness to work with me, the completion of this dissertation would not have been possible. I wish them even more success with their future professional careers.

Professor Armen Hovakimian has selflessly dedicated himself to the advancement of the finance doctoral program and I have extensively benefited from his guidance. His willingness to find time within his busy schedule to listen and share is much appreciated. I would like to thank Professor Joseph Weintrop not just as a professor and an executive officer, but also as a mentor. His involvement in the program is invaluable to each of us and to the program as a whole. I am grateful to Professor Nusret Çakıcı for kindly agreeing to be in my dissertation committee. I thank Professor Aloke Ghosh for his significant contribution to my research efforts. Professor Kishore Tandon has supported me extensively since my acceptance into the program. Professor Stephen Brown from New York University has kindly shared his probability of informed trading data. Finally, I am indebted to Professor Linda Allen, Professor Archishman Chakraborty and Professor Robert Schwartz for their efforts to advance my understanding of the field.

I would also like to express my deepest gratitude and love for my friends – Büke, Çağıl, Çağla, Deniz, Duygu, Gülru, Mehmet, Onur, Özge, Serhat and Sinem. Their presence in my life

have made the years I spent in the doctoral program joyful and gave me hope. Allison, Eleni, Guangzhong, Jason, Mike, Nosa, Sıla and Sylvia made me look forward to come to Baruch every day by their friendship and support. I have named only a few, and I apologize sincerely to the people I omitted.

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CHAPTER 1

A Brief Review of the Informational Role of Option Markets

Under standard option pricing models, an equity option's price is dictated by the price of the underlying stock. However, in incomplete markets, option prices may convey information about future stock returns if informed traders have a preference for the option market as a trading venue. Black (1975) suggests that option markets provide better opportunities for traders to exploit their private information compared to stock markets. First, for some types of options, brokerage commissions may be lower and liquidity greater when compared to an equivalent investment in the underlying stock resulting in reduced trading costs. Second, option markets enhance the opportunities for taking short positions in response to bad news by limiting potential losses. Moreover, since there is no uptick rule governing short sales of options, an investor who is prohibited from short-selling a stock on a down tick can instead short its equivalent in options.[1] Third, margin requirements may often prohibit a stock investor from obtaining a desired amount of leverage and this position can be realized by investing in options instead. Black writes "since an investor can usually get more action from a given investment in options than he can by investing directly in the underlying stock, he may choose to deal in options when he feels he has an especially important piece of information." Finally, investors who have private

[1] The uptick rule refers to a trading restriction that prohibits the short selling of securities except on an uptick. The rule became effective in 1938 but was removed when Rule 201 Regulation SHO went into effect in 2007. However, the reintroduction of the rule was widely discussed in 2009 and the SEC included a proposal for the reintroduction of the rule in a public comment published in April 2009.

information about the volatility of the underlying stock prices can only use this information by trading options.[2]

This chapter aims to provide a brief summary of the major studies that investigate the empirical evidence regarding the lead-lag relation between option and stock markets and the existence of informed trading in the option markets. Section 1 focuses on early research that uncovers evidence supporting the idea that option markets lead stock markets. Section 2 summarizes the subsequent evidence conflicting with and supporting these early studies. Section 3 covers the recent research in the area.

1. Early Research

In one of the pioneering empirical studies related to the lead-lag relations between option and stock markets, Manaster and Rendleman (1982) investigate the role of call option prices as predictors of the prices of their underlying stocks. The price of a European call option can be expressed with a closed-form formula using the Black-Scholes (1973) model. If S is the spot stock price, K is the exercise price of a call option, $(T-t)$ is the time to maturity, r is the risk-free rate per unit of time, σ is the standard deviation in the log-returns of the underlying stock and $N(\cdot)$ is the cumulative normal density function, the call option price, C, is equal to

$$C = SN(Z_1) - Ke^{-r(T-t)}N(Z_2) \tag{1}$$

where

[2] Ni, Pan and Poteshman (2008) find that non-market maker demand for volatility constructed from the trading volume of individual equity options is informative about the future realized volatility of underlying stocks.

$$Z_1 = \frac{\ln(S_0/K) + \left(r + \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}}$$

$$Z_2 = Z_1 - \sigma\sqrt{T-t} \quad .$$

The authors make adjustments to the above formula for dividend paying stocks. They also exclude options that can be optimally exercised prior to maturity and options with less than thirty days to maturity from the sample to abstract from the sensitivity of the Black-Scholes (1973) model to its underlying assumptions. Although the implied stock price, S^*, can be estimated using numerical techniques to invert equation (1), the implied stock price cannot be determined from the price of a single option since the volatility of a stock cannot be observed and estimates of volatility based on historical return data might be inaccurate. Therefore, the authors use data from several options to solve the following problem for the implied stock price, S^*, and implied standard deviation, σ^*, simultaneously for each stock *j:*

$$\left(S_j^*, \sigma_j^*\right) = \arg\min[Q(S_j, \sigma_j) = \sum_{i=1}^{N_j}[C^i - C^i(S_j, \sigma_j)]^2] \qquad (2)$$

where C^i is the observed option price, $C^i(S_j, \sigma_j)$ is the calculated Black-Scholes (1973) option price and N_j is the number of options written on stock *j*. The solution to this expression minimizes the sum of squared deviations between observed and calculated option prices. The authors define a proportional error which is equal to $\left(S_j^* - S_j\right)/S_j$, the difference between the implied and observed stock price scaled by the observed stock price. In a regression of one-day ahead stock returns on the one-day ahead market returns and lagged proportional errors, the coefficient of the proportional error turns out to be significantly positive. The authors interpret this result as evidence for options prices including incremental information that does not get reflected in stock prices up to one day. In a similar study, Bhattacharya (1987) again inverts the Black-Scholes (1973) model to obtain implied stock prices. If the absolute differences between the observed stock price and the implied stock price are greater than a certain threshold, an arbitrage opportunity is recognized. The author devises ex-ante trading strategies based on these arbitrage opportunity signals to test the null hypothesis that the stock and option markets are synchronous. An added benefit of this study is that, in contrast to Manaster and Rendleman (1982) who use closing prices in each market, Bhattacharya (1987) uses intra-day observations of bid and ask prices on both the call options and the stocks to estimate possible arbitrage opportunity magnitudes more precisely. The results show that the null hypothesis is rejected and option prices contain information that is not reflected in contemporaneous stock prices, albeit insufficient to overcome the bid-ask spreads for intra-day holding periods.

Jennings and Starks (1986) conjecture that if some traders believe that the option market provides a superior investment vehicle and they execute their trades using option positions as a substitute for stock positions, then these option trades may move option premia out of equilibrium relative to the underlying equity prices. In this case, arbitrageurs will intervene to realign the prices in the two markets and thus, the option market might play a role in the determination of stock values. The authors test this conjecture by focusing on the adjustment of stock prices to information releases. More specifically, they use a control portfolio methodology based on investor interest, trading activity and price volatility and compare the price adjustment processes of firms with and without exchange-listed options during earnings announcements. They demonstrate that the stock price adjustment to new information occurs more rapidly for firms with listed options and interpret this result as evidence for the informational role of option markets.

Anthony (1988) looks at the lead-lag relations between call option and stock trading volumes rather than focusing on price processes. The relation between the absolute value of price changes and volume is positive if one accepts a sequential-information-arrival hypothesis. The author hypothesizes and tests the sequential flow of information between the stock and option markets by analyzing the Granger (1969) causality between trading volumes in the two markets. If information trading occurs predominantly in one of the markets, then one would expect to see a lead-lag relation between option and stock trading volumes. The results indicate that option trading volume leads stock trading volume with a one-day lag.

2. Conflicting and Supporting Evidence

The early evidence for the leading role of the option markets has been scrutinized extensively by subsequent studies. Vijh (1988) argues that the non-synchronicity of the closing stock and option trade prices used in Manaster and Rendleman (1982) introduces severe biases in their empirical analysis. Moreover, these biases will arise whenever only trade prices are used, whether or not they are the last prices for the day, due to the existence of the bid-ask bounce. First, a positively biased proportional error may result when the closing stock price is a bid price and therefore too low compared with the true stock price, which should have been used to calculate the proportional error. Second, due to the non-synchronicity of closing stock and option trades, a positively biased proportional error may occur if the closing stock price is lower than the price prevalent in the stock market at the time the options are last traded. Due to either influence, the contemporaneous return would be understated whereas the proportional error and the one-day ahead return would be overstated. Conversely, when the closing stock price is too high, either because it is an ask price or it is greater than the price prevalent in the stock market at the time the options are last traded, both the proportional error and the one-day ahead return would be understated. As a result, the coefficient on the proportional error in the regression of one-day ahead stock returns might turn out to be significantly positive even when the true contemporaneous stock and option prices contain the same information. In other words, the results in Manaster and Rendleman (1982) might be spurious.

Stephan and Whaley (1990) use a different approach to circumvent the problems of previous studies. First, they use transaction-by-transaction data from the stock and option markets so that the biases inherent in the non-synchronicity of closing prices in the two markets are avoided. Second, unlike Bhattacharya (1987), their analysis focuses directly on the lead-lag relation between the intra-day price changes in the stock and option markets rather than indirectly through a simulated trading strategy. The changes in call prices over five-minute intervals are transformed into implied stock price changes and then multivariate time series regressions are used to estimate the lead-lag relations between the price changes in both markets. Their results contradict earlier empirical findings and indicate that the stock market leads the option market by as much as fifteen minutes, both in terms of price changes and trading activity.

Finucane (1999) follows Stephan and Whaley (1990) and builds on their empirical approach. The time interval between stock and option market quote formation and dissemination to other exchanges is typically measured in seconds and quotes in one market can be reflected in quote changes in other markets almost instantaneously. Since there are very minimal direct costs associated with changing quotes, any systematic leads between the stock and option markets will be shorter than five minutes. Using five-minute intervals, as in Stephan and Whaley (1990), will obscure any leads less than five minutes. However, fixed intervals short enough to measure leads less than five minutes will create serious biases since the frequency of stock and option transactions might be low. To overcome this problem, Finucane uses ordered quote changes in the stock and option markets to construct variable-length price change intervals. The stock-quote and option-quote intervals are constructed whenever a new quote is registered so that the length of each interval is determined by the actual time between quotes. Quotes in both markets are seldom recorded during the same second, thus whether an option quote or stock quote is recorded first can be almost always determined. This empirical approach enables the author to unambiguously determine whether stock-quote changes precede or follow option-quote changes. The findings indicate that stock quotes tend to lead option quotes, but the length of the lead is less than those in Stephan and Whaley (1990), ranging from a few seconds to six minutes.

Chan, Chung and Johnson (1993) use a nonlinear system equations model where five-minute price changes of call options are regressed on lagged, contemporaneous and leading five-minute underlying stock price changes. This approach is simpler than estimating implied stock prices used in earlier studies as it requires less information to be implemented. The results confirm the results of Stephan and Whaley (1990) and show that the stocks lead the call options by fifteen minutes. However, the empirical approach also provides an explanation for the puzzling lead of stocks over options. Before the decimalization of security prices, the minimum tick for a stock is typically one-eighth. The minimum tick for options with prices greater than three dollars is also an eighth, but this entails a larger percentage move in the option prices. Thus, small moves in the stock price may not be immediately reflected in the option prices because the changes in the theoretical value of the option would be less than the tick and the option wouldn't trade. This would cause the stock market to spuriously lead the option market. The authors look further into this idea and find that the lead of the stock market vanishes under circumstances when a lead should not be observed, e.g. the stock price change is large enough.

Moreover, since the option tick is important in understanding the stock market lead, the authors look at bid-ask quote data as well as transaction prices. Although bid and ask quotes are also discrete, the option market maker can adjust either the bid or the ask or both without waiting for an order to arrive. The authors find that the lead of the stock market vanishes when the tests are run using the average of the bid and ask prices rather than transaction prices lending more support to the idea that the stock market lead is spurious.

Although none of these studies find that the option market leads the stock market, there were also some concurrent studies which lent support to the findings of the earlier studies that attributed an informational role to the option markets. Sheikh and Ronn (1994) are motivated by the idea that understanding the similarities and differences in return patterns across different securities and market structures can help in the development of better return models that capture these properties. For example, finding independent and different patterns in the stock returns in NYSE and option returns in CBOE may lead to an identification of exchange and/or security specific characteristics that drive security returns. Although options are redundant assets in a perfect market, Back (1993) questions this hypothesis by attributing differential information to the purchase of options' nonlinear payoffs. Thus, the existence of informed trading in options may induce components in option returns that are independent of the returns of their underlying stocks. Moreover, strategic behavior by informed traders and discretionary transactions of liquidity traders can induce systematic patterns in the option returns' independent components. Sheikh and Ronn (1994) uncover patterns in option returns that are not replicated in stock returns even after adjusting for mean and variance patterns of the underlying assets. Their interpretation is that informed trading in options can make the order flow in the option markets informative about the values of the underlying assets.

Fleming, Ostdiek and Whaley (1996) conjecture that trading index options has particularly lower transaction costs than trading in the underlying stocks constituting the index. This is in contrast to individual equities. Therefore, they expect to find that S&P 100 index options lead the underlying S&P 500 index and their results confirm this expectation. Finally, Diltz and Kim (1996) analyze time-stamped bid and ask prices for both options and stocks instead of transaction prices. For each stock and trading day, the actual stock quote bid price and Black-Scholes (1973) implied midprice derived from option quotes are analyzed. The authors synchronize the quotes from NYSE and CBOE by extracting the last quotes prior to 3 PM. Using vector error correction models, they find that there is a bidirectional causality in the short-run price dynamics between the two sets of co-integrated prices.

3. Recent Research

The evidence related to the informational role of options in price discovery has been mixed up to this point. Easley, O'Hara and Srivinas (1998) make an important theoretical contribution to this literature by setting up a sequential trading model to understand what trading venue the informed traders choose. They identify conditions of a pooling equilibrium in which informed traders would direct their trades to the option markets. The theory predicts that if option markets are venues for information-based trading, then option trades of various types should convey information about future stock price movements. The model suggests that the price discovery role of option markets should be more pronounced when the liquidity of the option market is higher compared to that of the stock market, when options provide higher leverage and when the probability of informed trading is high.

After this theoretical contribution to the literature, empirical researchers started to uncover more evidence that option markets are venues for information discovery. Chan, Chung and Fong (2002) set up vector autoregression models for multiple markets where they test the effect of net trade volumes and returns of options and of stocks on each other using intra-day data. They find that stock net trade volume, defined as the buyer-initiated minus seller-initiated volume, has strong predictive ability for stock and option quote revisions. On the other hand, both stock and option quotes have predictive ability for each other. The takeaway is that information in the option market is contained in quote revisions whereas information in the stock market is contained in both quote revisions and trades.

Chakravarthy, Gulen and Mayhew (2004) investigate the contribution of option markets to price discovery using a modification of Hasbrouck's (1995) information share approach. Specifically, they use a methodology that measures the contribution of the innovation in the pricing process of the option market to the total variance of the innovation in the permanent component of the price vector spanning both stock and option markets. Based on five years of stock and options data for sixty firms, they estimate the option market's contribution to price discovery to be about 17% on average. Consistent with the predictions of Easley, O'Hara and Srivinas (1998), option market price discovery tends to be greater when the option volume is higher related to stock volume and when the effective bid-ask spread in the option market is narrow relative to the spread in the stock market.

Cao, Chen and Griffin (2005) focus on takeover announcements to investigate the market preference of investors prior to extreme informational events. In normal times, buyer-seller initiated stock volume imbalances are predictors of next-day stock returns but option volume imbalances are uninformative. However, call-volume imbalances become strong predictors of next-day stock returns prior to takeover announcements. Moreover, targets with the highest returns during takeover announcements experience the largest pre-announcement call imbalance increases. These findings suggest that the option markets play an important role in price discovery before information events.

As Easley, O'Hara and Srivinas (1998) propose, informed traders are not entirely indifferent to factors such as option moneyness, degree of information asymmetry and option liquidity in deciding where to place their trades. Chen, Lung and Tay (2005) argue that earlier studies suffer from the fact that they do not control for the effect of option moneyness on option liquidity and leverage. The authors isolate a subsample of firms that have a high level of information asymmetry and find out-of-the-money options to be the most liquid options with the highest delta-to-premium ratios, in general. After controlling for factors such as moneyness and liquidity, they discover feedback relations between trades in out-of-the-money options and their underlying stocks. This finding is consistent with a pooling equilibrium where informed traders trade in both the stock and option markets.

Pan and Poteshman (2006) use a proprietary data set to construct put-volume over call-volume ratios from option volumes initiated by buyers to open new positions. In their portfolio analysis, they find that stocks with low put-call ratios outperform stocks with high put-call ratios by more than 1% over a one-week horizon. They also present extra evidence supporting the idea that this predictability is driven by informed trading in the option markets. First, when the option signals are partitioned into components that are publicly and non-publicly observable, the economic source of the predictability turns out to be private information possessed by option traders rather than market inefficiency. Second, the predictability is stronger for stocks with higher concentrations of informed traders and for options that offer higher leverage.

Bali and Hovakimian (2009) use a VAR-bivariate-GARCH framework to model information flow between the stock and option markets. The VAR-bivariate-GARCH model enables the investigation of lead-lag relations, or information spillover effects, in both the conditional means and conditional variances. The authors find that lagged squared shocks to the stock and option price processes affect the conditional stock return variance. However, the conditional variance of option returns is only affected by the lagged squared option return shocks and the lagged variance of option returns. The interpretation of these results is that investors with private information are active in the option market.

Finally, Cremers and Weinbaum (2010) focus on a different aspect of the option markets, namely deviations from put-call parity. They argue that put and call option prices can deviate from model values due to the activities of informed traders in the option markets. The authors measure deviations from put-call parity by the implied volatility spreads between matched put and call options and find positive abnormal performance for stocks with relatively expensive calls and negative abnormal performance for stocks with relatively expensive puts.

CHAPTER 2

Is It Skewness or Information in Volatility Spreads that Predict Market Returns?

1. Introduction

This study investigates the intertemporal relation between implied volatility spreads of S&P 500 index options and expected returns on the aggregate stock market and provides evidence for a negative link between volatility spreads and expected market returns. This negative relation is highly significant through time and robust under different specifications, estimation methodologies, and alternative measures of volatility spreads.

Theories investigating the information flow from option markets to stock markets and demand-based option pricing models suggest a linkage between volatility spreads and expected returns. In the sequential trade model of Easley, O'Hara and Srinivas (1998), uninformed liquidity traders trade in both the equity market and the options market for exogenous reasons, whereas informed traders must decide whether to trade in the equity market, the options market, or both. Easley, O'Hara and Srinivas (1998) show that if some informed investors choose to trade in options before they trade in the underlying stock, possibly because of the leverage that options offer, then changes in option prices (i.e., spreads in call and put options' implied volatilities) can carry information that is predictive of future stock price movements (see Xing, Zhang, and Zhao (2009), Bali and Hovakimian (2009), and Cremers and Weinbaum (2010)).

In the demand based option pricing models of Bollen and Whaley (2004) and Garleanu, Pedersen and Poteshman (2009), when the demand for particular option contracts is strong, competitive risk-averse option market makers are not able to hedge their positions perfectly and they require a premium for taking this risk. As a result, the demand for an option affects its price. In this type of equilibrium, one would expect a positive relationship between option expensiveness which can be measured by implied volatility and end-user demand. Investors with positive (negative) expectations about the future stock prices will increase their demand for calls (puts) or reduce their demand for puts (calls), implying an increase in call (put) option volatility or decrease in put (call) option volatility. Therefore, if the put minus call implied volatility spread becomes lower (higher), this implies an increase (decrease) in the expected future price of the underlying stock (i.e., higher (lower) expected returns). Based on the implications of both the information flow story of Easley, O'Hara and Srivinas (1998) and the demand based option pricing models, I expect a negative relation between put minus call volatility spreads and expected market returns.

An alternative explanation for a significant link between volatility spreads and expected market returns is skewness. Xing, Zhang and Zhao (2009) interpret the slope of the option volatility smirk, measured as the volatility spread between out-of-the-money (OTM) put and at-the-money (ATM) call options, as a proxy of total skewness. Starting with Arditti (1967), financial economists have theorized a negative relationship between expected returns and co-skewness (or systematic skewness). Investors prefer higher skewness, therefore they are willing accept lower returns for holding assets that increase the skewness of their portfolios. Rubinstein (1973) and Kraus and Litzenberger (1976) develop general equilibrium models where an individual security's contribution to the skewness of the market portfolio becomes a component of the security's expected returns. A more recent strand of literature theorizes that idiosyncratic skewness is also a determinant of expected returns. Brunnermeier, Gollier and Parker (2007) and Barberis and Huang (2008) introduce theoretical models in which investors exhibit behavioral biases and the idiosyncratic skewness of each security is negatively related to its expected return.[3] In light of these literatures, it might be the case that a negative relation between volatility spreads and expected market returns is driven by the effect of conditional skewness on expected returns.

This is the first study to investigate the intertemporal relation between volatility spreads and expected returns for the aggregate market. Merton's (1973) intertemporal capital asset pricing model (ICAPM) suggests that the conditional mean and conditional volatility of excess returns on the market portfolio should be positively related. To test the relation between volatility spreads and expected market returns, I augment the ICAPM framework by adding various volatility spread measures. To construct the measures of volatility spreads for S&P 500 index options, I follow Xing, Zhang and Zhao (2009). Specifically, the volatility spread measures are equal to the implied volatility difference between OTM put options and ATM call options on the S&P 500 index.[4] The sample period is from January 4, 1996 to September 10, 2008. Since there are multiple OTM put and ATM call options being traded on a given day, I use different methods to calculate a single measure of the implied volatility spread in each day.

The main result is that volatility spreads are significantly and negatively related to future excess returns on the market. I investigate the predictive power of volatility spreads for horizons

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[3] A limited amount of empirical work tests this negative relationship in a cross-sectional framework and finds that stocks with higher total skewness have lower expected returns. See Mitton and Vorkink (2007), Boyer, Mitton and Vorkink (2009), and Kumar (2009).

[4] The slope of the volatility smile is commonly measured as the difference in implied volatilities between OTM put options and ATM put options. The results are robust to using this alternative measure. Xing, Zhang and Zhao (2009) use ATM call options instead of ATM put options since ATM calls have higher trading volumes than ATM puts.

ranging from one day to three months and find that there is a significantly negative link between volatility spreads and market returns for horizons up to one month. For example, when the daily implied volatility spread increases by 1%, the decrease in the excess return on the S&P 500 index is about 3.43% to 9.15% per annum depending on the method being used to measure volatility spreads.

In the empirical specification, I control for the conditional volatility of the market to make sure that the negative relation between volatility spreads and expected market returns is not driven by a possible correlation between conditional volatility and volatility spreads. The main conditional volatility measure that I use is the square of VIX, the options' implied volatility of the S&P 500 index obtained from the Chicago Board Options Exchange (CBOE).[5] I also control for a wide variety of state variables that proxy for the intertemporal hedging demand component of ICAPM. Macroeconomic variables such as the changes in the default and term spreads, the detrended riskless rate, and the aggregate dividend yield of the S&P 500 index are added to the empirical specification to capture the changes in the investment opportunity set. I find that the negative relation between the volatility spreads and expected returns is robust to the inclusion of conditional volatility measures and other controls in the specification.

Guo (2006) finds that accounting for time-varying risk aversion by using various macroeconomic forecasting variables significantly improves the performance of ICAPM. Motivated by this idea, I consider the possibility that the relation between volatility spreads and expected returns is also state-dependent and varies through time. To test the subsample stability of the results, I divide the entire sample period to many pieces and estimate the empirical

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[5] Other conditional volatility controls that considered in this paper are the realized variance of the S&P 500 index computed as the sum of squared 5-minute returns on a given day with an adjustment for the first-order serial correlation, and the range variance of the S&P 500 index returns based on the maximum and minimum values of the index on a given day.

specification using rolling regressions. The results from these subsample analyses indicate that the strong negative relation between volatility spreads and expected returns is robust over time.

I construct direct measures of conditional skewness using two distinct methods and show that the negative relation between volatility spreads and expected market returns is not driven by a potential negative link between conditional skewness and aggregate returns. First, I calculate physical skewness measures based on the physical return distribution of S&P 500 returns (i.e., using the past index return data). Skewness is not persistent and there is no agreed-upon method to calculate the physical measure of skewness. Nevertheless, I construct alternative conditional skewness estimates using one-month to twelve-month windows of past S&P 500 index returns. Second, I follow Bakshi, Kapadia and Madan (2003) who parametrically construct higher order moments of an underlying stock from a continuum of call and put options on the stock.[6] These risk-neutral conditional skewness estimates are potentially better measures of conditional skewness than physical skewness measures that come from the empirical distribution of index returns because options data already incorporate the market's expectation of future skewness. I find that neither physical skewness nor risk-neutral skewness measures have any robust relation with the expected excess returns on the market. These findings support the idea that it is information flow rather than skewness that drives the negative relation between volatility spreads and expected market returns.

To lend additional support to the information story, I look at the predictive power of volatility spreads after conditioning on the level of the consumer sentiment index. Lemmon and Portniagunia (2006) find that investor sentiment measured using the consumer confidence index is significantly related to stock returns. If implied volatility spreads contain information about

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[6] Bakshi, Kapadia and Madan (2003) theoretically and empirically show that risk-neutral skewness is related to the slope of the volatility smirk.

consumer sentiment, then one would expect the predictive power of volatility spreads to be stronger when consumer sentiment is unusually high or low. The empirical results confirm this conjecture.

The paper is organized as follows. Section 2 describes the data and estimation methodology. Section 3 presents the empirical results. Section 4 runs a battery of robustness checks. Section 5 concludes.

2. Data and Estimation Methodology

Merton (1973) suggests that the conditional expected excess return on the aggregate market should be a linear function of the aggregate market's conditional volatility plus a hedging component which proxies for the investor's desire to hedge for unfavorable shifts in the investment opportunity set. Moreover, the relationship between the conditional excess return and the conditional volatility should be positive. The coefficient of the conditional variance can be interpreted as the coefficient of relative risk aversion. This model has been tested extensively in the literature. Earlier studies on ICAPM differ in the methods they use to model conditional volatility and the future return horizons and past conditional volatility windows they focus on. The evidence from these studies is mixed as some papers find insignificant, even negative, coefficients of relative risk aversion. There are also some studies that provide evidence for a positive relation between the conditional expected return and the conditional volatility of the market.[7] In this study, to investigate the intertemporal relation between volatility spreads and expected market returns, I estimate the extended version of the ICAPM specification:

[7] See the recent papers by Guo and Whitelaw (2006), Lundblad (2007), and the references therein.

$$R_{t+1} = \alpha + \gamma \cdot E_t[VAR_{t+1}] + \beta \cdot VS_t + \theta \cdot X_t + \varepsilon_{t+1} \quad (1)$$

where R_{t+1} is the excess return on the market portfolio (S&P 500 index) at time t+1, $E_t[VAR_{t+1}]$ is the time-t expected conditional variance of the market portfolio return, VS_t is the measure of volatility spread at time t, and X_t denotes a set of macroeconomic variables associated with business cycle fluctuations.

The sample period is from January 4, 1996 to September 10, 2008, yielding a total of 3,189 trading days. The estimate for the expected return on the left-hand side of equation (1) is the one-period ahead excess return on the S&P 500 index obtained from the Center for Research in Security Prices (CRSP). The excess return on period t+1 is measured as the excess return from the closing index level on period t to the closing index level on period t+1.[8] Equation (1) is estimated for different return horizons. Specifically, the dependent variable is replaced by the one-day, one-week, two-week, one-month and three-month ahead excess market returns one at a time.

The variable of interest is the volatility spread (*VS*). Following Xing, Zhang and Zhao (2009), I use the implied volatility difference between OTM put options and ATM call options to measure *VS* (or the slope of the volatility smile). The data on the implied volatilities of S&P 500 index options are obtained from the IvyDB database of OptionMetrics which provides implied volatility, end-of-day bid-ask quotes, open interest and volume information for all exchange traded options. This dataset begins in 1996. Moneyness is defined as the ratio of the strike price

[8] Battalio and Schultz (2006) argue that ignoring the non-synchronicity between the option and stock markets can bias empirical results. The option market closes two minutes later than the stock market and a significant relation between volatility spreads and one-period ahead market returns may simply reflect this fact. To rule out this possibility, I calculate the one-period ahead index returns starting from the opening of the next trading day in unreported tests. All the results in this paper remain intact.

to the stock price. A put option is defined as OTM if its moneyness is lower than or equal to 0.95, but higher than or equal to 0.80. A call option is defined as ATM if its moneyness is between 0.95 and 1.05. I also adopt various screens from Xing, Zhang and Zhao (2009) and drop an option from the sample if its annualized implied volatility is less than 3% or more than 200%, if its time to expiration is less than 10 days or more than 60 days, if its open interest is negative, if its price is less than $0.125 or if its volume data is missing.[9]

Since there are multiple OTM put and ATM call options being traded on a given day, I use different methods to calculate a single measure of implied volatility for OTM put and ATM call options in each day. HVVS is the implied volatility difference between the OTM put option and the ATM call option that have the highest volumes. HOVS is the implied volatility difference between the OTM put option and the ATM call option that have the highest open interests. VWVS is the difference between volume-weighted average implied volatility of all OTM put options and volume-weighted average implied volatility of all ATM call options. OWVS is the difference between open interest-weighted average implied volatility of all OTM put options and open interest-weighted average implied volatility of all ATM call options.

The descriptive statistics for the volatility spread measures are presented in Panel A of Table 1. As can be seen, the mean and median volatility spread measures are positive indicating that the S&P 500 put options were more expensive than the S&P 500 call options on average. For the highest open interest and highest volume volatility spread measures, the standard deviations are about half of the mean and median volatility spreads. For the open interest and volume weighted volatility spread measures, the standard deviations are about a quarter of the mean and median volatility spreads. The skewness and kurtosis estimates of the volatility spread

[9] The results are robust to the removal of these individual screens.

measures indicate that the volatility spreads are mildly right-skewed and extreme deviations from the median are rare.

The main measure used to control for the relationship between conditional volatility and conditional expected returns in equation (1) is VIX. VIX is the implied volatility which measures the market's forecast of the volatility of the S&P 500 index and is downloaded from the CBOE's website. VIX is obtained from the European style S&P 500 index option prices and incorporates information from the volatility smile by using a wide range of strike prices. The implied variance denoted by VIXSQ is equal to the square of VIX. In some specifications, I use alternative measures of conditional volatility. RANGEVAR is the range volatility defined as the square of the difference between the logarithm of the highest price and the logarithm of the lowest price in each period as in Alizadeh, Brandt and Diebold (2002) and Brandt and Diebold (2006). This measure of volatility is highly efficient, robust to microstructural noise and approximately Gaussian. REALVAR is the realized variance calculated as the sum of squared five-minute returns adjusted for autocorrelation as in Andersen, Bollerslev, Diebold and Ebens (2001) and Andersen, Bollerslev, Diebold and Labys (2003). The intra-day price data are obtained from Olsen Data Corporation.

To make sure that the results are not affected by model misspecification, I add a set of control variables (X_t) that are expected to have an empirical relation with the excess market returns. There is a large body of literature indicating that the aggregate returns can be predicted by macroeconomic variables associated with business cycle fluctuations. These variables also control for the hedging demand component in Merton's (1973) ICAPM. DEF is the change in the default spread calculated as the change in the difference between the yields on BAA- and AAA-rated corporate bonds. TERM is the change in the term spread calculated as the change in the difference between the yields on the 10-year Treasury bond and one-month Treasury bill. RREL is the detrended riskless rate defined as the yield on the one-month Treasury bill minus its one-year backward moving average. DP is the daily dividend price ratio as calculated in Fama and French (1988) using the returns on the S&P 500 index with and without dividends.[10] Finally, I include the lagged return on the S&P 500 index to control for the serial correlation in index returns.

3. Empirical Results

3.1. Intertemporal Relation between Volatility Spreads and Market Returns

Table 2 presents results from the time-series regressions of one-period ahead excess returns of the S&P 500 index on various volatility spread measures and control variables as in equation (1). The analysis in Table 2 is essentially a test of an extended version of Merton's (1973) ICAPM. Merton argues that an asset's expected return has to be positively related to its conditional variance, therefore I expect to find significantly positive slope coefficients for the conditional variance measures. These coefficients can be interpreted as the relative risk aversion parameters. The hedging demand component in ICAPM is controlled by various macroeconomic variables. The first row in each regression gives the intercepts and slope coefficients. The second row presents the Newey-West (1987) adjusted *t*-statistics.[11] The same model is estimated for expected market returns associated with different time horizons ranging from one day ahead to three months ahead.

[10] The time-series data on 10-year Treasury bond yields and BAA- and AAA-rated corporate bond yields are available in the Federal Reserve statistics release website. Yields on the one-month Treasury bill are downloaded from Kenneth French's online data library.

[11] The results are robust to different lags used in the Newey-West estimation.

The first set of results in Table 2 pertain to the regression of one-day ahead excess market returns on lagged volatility spreads and control variables. The results show that all volatility spread measures have significantly negative coefficients, reflecting the fact that when put options are relatively more expensive with respect to call options written on the S&P 500 index, one-day ahead market returns are more negative. The coefficients of the volatility spread measures range from -0.0136 to -0.0363, implying considerable economic significance as well: when volatility spreads increase by 1%, one-day ahead excess market returns decrease by 1.36 to 3.63 basis points, which corresponds to 3.43% to 9.15% per annum assuming 252 trading days in a year. The coefficient of HVVS (OWVS) has the lowest (highest) statistical significance with a *t*-statistic of -2.98 (-4.33).

For the longer horizon return regressions, volatility spreads, VIXSQ, RREL and DP are measured at the end of the period before returns begin to accumulate whereas RET, DEF and TERM are measured over the period before returns begin to accumulate. In the next set of regressions, I replace the dependent variable with one-week ahead excess market returns. As can be seen, the coefficients of the volatility spread measures are still significantly negative ranging from -0.0235 to -0.1006. In other words, when volatility spread measures increase by 1%, one-week ahead excess market returns decrease by 2.35 to 10.06 basis points. Extending the measurement window for expected market returns to two weeks or one month does not take away the negative significance of the volatility spread measures. For the two-week horizon, the coefficient of VWVS (OWVS) has the lowest (highest) statistical significance with a *t*-statistic of -1.97 (-2.79) whereas for the one-month horizon, the coefficient of VWVS (HVVS) has the lowest (highest) statistical significance with a *t*-statistic of -1.96 (-2.55). The significantly negative link between volatility spreads and expected market returns vanishes when the return measurement horizon is extended to three months. The coefficients of all volatility spread measures become insignificantly negative and the most negative *t*-statistic is associated with VWVS (-1.28). These results collectively suggest that volatility spreads can predict excess market returns and this predictability extends to a horizon of one month.

The results show that implied variance measured by VIXSQ is positively and significantly related to one-period ahead excess S&P 500 returns. In the regressions of one-day ahead excess market returns, the estimated coefficients on the lagged implied volatility range between 6.6450 and 7.3331. The *t*-statistics associated with these relative risk aversion parameters range between 2.28 and 2.49.[12] When the excess returns are extended to longer horizons, the significance of the coefficient of VIXSQ remains intact. For horizons up to three months, all of the coefficients of the implied variance are significantly positive and the relative risk aversion parameters vary between 4.6346 and 6.0100.

Without the macroeconomic controls, in the one-day ahead return regressions, the coefficients of volatility spreads range between -0.0120 and -0.0332 with associated *t*-statistics that vary between -2.72 and -4.07 (unreported). With the addition of the macroeconomic variables, the noise in the index returns is reduced and, if anything, the negative relation between volatility spreads and expected market returns becomes stronger. One can also see that the estimated coefficients on the macroeconomic variables are insignificant with the exception of the dividend-price ratio. It seems that most of the variables that proxy for future investment opportunities have no relation with excess market returns. The detrended riskless rate also becomes significant for longer term index returns and the change in the term premium is significant for the two-week horizon.

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[12] All results presented for the implied variances in this paper also hold for the realized and range variances, and they are available upon request from the author.

3.2. Intertemporal Relation between Physical Skewness and Market Returns

The literature on the relation between skewness and expected returns dates back to Arditti (1967). In a Taylor series expansion of the utility function around expected future wealth, the third moment of future wealth becomes a priced factor. Moreover, Arditti shows that for a risk-averse investor with non-increasing absolute risk aversion, this third moment, which can be interpreted as a measure of co-skewness, has to be negatively related to expected returns. Therefore, investors prefer assets that add to the skewness of their portfolios, i.e., risk-averse investors would be more (less) reluctant to take investments that might bring large losses (gains) with limited gains (losses) and they would accept lower expected returns from investments with higher co-skewness. Rubinstein (1973) and Kraus and Litzenberger (1976) develop more elaborate general equilibrium models where the representative investor adjusts her portfolio such that the expected return on each risky security is equal to the risk-free rate plus a premium that is equal to the weighted sum of the co-moments of the expected return of the security with the investor's future wealth. In these models, the marginal rate of substitution between expected return and skewness times the risky asset's marginal contribution to the skewness of the market portfolio becomes a component of the risky asset's expected return. Harvey and Siddique (2000) introduce a similar model that focuses on the conditional co-skewness rather than unconditional co-skewness. They also document a negative relationship between individual securities' expected returns and the returns on a factor-mimicking portfolio based on conditional co-skewness. The common theme of these studies is that co-skewness or systematic skewness is a potentially important determinant of expected returns.

More recently, another strand of literature has emerged that examines the role of idiosyncratic skewness in explaining security returns. Barberis and Huang (2008) build on the cumulative prospect theory of Tversky and Kahneman (1992) to produce novel asset pricing implications. In their model, investors use a transformed probability weighting function and overweight the tails of the return distribution. When positively skewed securities are introduced into the economy, even in the absence of heterogeneous beliefs, there can be non-unique globally optimum portfolio holdings. As a result, some investors find it beneficial to hold a large, undiversified position in the skewed securities and accept a negative excess return on such assets.[13] Brunnermeier and Parker (2005) and Brunnermeier, Gollier and Parker (2007) arrive at similar predictions based on a model of optimal expectations. They argue that investors derive current felicity from expected future utility flows, thus they are happier if they overestimate the probabilities of the world in which their investments pay off well. In essence, investors form subjective beliefs that trade off the expected benefits of anticipatory utility against the costs of basing investment decisions on biased beliefs. In the model, investors choose to be optimistic about the states with the most positively skewed returns, therefore they overinvest in the most skewed assets. In the general equilibrium, due to heterogeneous beliefs, their portfolios have idiosyncratically skewed returns and their skewness preferences have asset pricing effects. Kumar (2009) investigates the portfolio holdings of a group of individual investors and finds that investors who invest disproportionately more in stocks with high idiosyncratic skewness exhibit greater underperformance. In summary, economic theories based on behavioral biases predict a negative relationship between idiosyncratic skewness and expected returns.

[13] Mitton and Vorkink (2007) model heterogeneity in skewness preference and argue that this heterogeneity contributes to underdiversification. They also document that some investors are trading off mean-variance efficiency for holding more positively skewed portfolios. Goetzmann and Kumar (2009) also document that less diversified investors overweight stocks with greater skewness in their portfolios.

To see whether the negative link between volatility spreads and expected market returns is due to an intertemporal relation between conditional skewness and expected market returns, I attempt to construct more direct measures of skewness. Although Xing, Zhang and Zhao (2009) interpret the slope of the volatility smirk (i.e. OTM put implied volatility minus ATM call implied volatility) as a proxy for skewness, this is only an indirect and noisy measure. Measuring conditional skewness is complicated. First, past skewness is not an accurate predictor of future skewness because skewness is not persistent over time. Moreover, skewness is associated with small probability events that are difficult to capture within a short period of time. Thus, a long history of returns is necessary to obtain accurate skewness estimates and this brings severe data constraints and survivorship bias to empirical studies. To circumvent these problems, Boyer, Mitton and Vorkink (2009) follow Chen, Hong and Stein (2001) and generate expected skewness measures using a number of firm variables to test the significance of a cross-sectional relation between expected skewness and stock returns. Since my study is at the aggregate level, this approach cannot be used.

There is no econometric theory that derives accurate and efficient estimators of higher-order moments from the empirical return distribution. Nevertheless, I attempt to construct physical skewness measures and test their predictive power for future market returns. Andersen et al. (2001, 2003) prove that realized volatility calculated from squared intra-day returns is an efficient and consistent measure of daily volatility under the assumption of log-normality. However, no such theory exists for skewness. Even so, I imitate their method and construct four distinct measures of physical skewness. Specifically, PSKEW1M is equal to the skewness of the daily S&P 500 returns over the past month. Similarly, PSKEW3M, PSKEW6M and PSKEW12M are equal to the skewness of the daily S&P 500 returns over the past three months, six months and twelve months, respectively. Panel B of Table 1 presents descriptive statistics for these physical skewness measures. The means and medians of the physical skewness measures are negative, albeit small in magnitude. The standard deviations are also much larger than the means and medians. It can also be seen that the physical skewness measures are mildly left-skewed and do not have fat tails.

Table 3 presents results from the time-series regressions of the excess market returns on the physical skewness measures, conditional volatility and macroeconomic control variables. The dependent variable in the first set of regression results is one-day ahead excess market returns. None of the physical skewness measures have significant coefficients and the *t*-statistics range between -1.11 and 0.21. This result remains intact for longer horizons over which expected market returns are measured. In all of the specifications, all four physical skewness measures have insignificant coefficients. In this table, the control for the conditional variance is REALVAR since it is also derived from the empirical distribution of index returns.[14] The coefficient on REALVAR is significantly positive in all of the specifications for all return measurement horizons. The relative risk aversion parameters range between 5.2356 and 5.3219 for one-day ahead return regressions and between 1.1341 and 1.2231 for three-month ahead return regressions. The lowest *t*-statistic associated with the relative risk aversion parameters in Table 3 is 2.02 whereas the highest *t*-statistic is 4.05. None of the macroeconomic variables have significant coefficients with the exception of the term premium and the detrended riskless rate that gain positive significance in the two-week horizon.

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[14] The results are the same when range variance is used to control for conditional variance rather than realized variance.

3.3. Intertemporal Relation between Risk-Neutral Skewness and Market Returns

In this section, I construct risk-neutral skewness measures based on the method of Bakshi, Kapadia and Madan (2003) to see whether a negative link between risk-neutral skewness and expected market returns is responsible for the negative intertemporal relation between volatility spreads and aggregate returns. One might expect risk-neutral skewness measures derived from option prices to be more accurate proxies of expected skewness as option data already incorporate the market's expectations about future skewness. Bakshi, Kapadia and Madan (2003) argue that there is no natural way to reconstruct the risk-neutral density from its higher moments and even when option models are well-enough specified across strike prices, any derived relation between option prices and risk-neutral moments might be just a reflection of the particular modeling choice. Thus, the authors derive risk-neutral moments calculated from model-independent equations that are free from the misspecification errors of option pricing models. Specifically, any payoff to a security can be constructed and priced using a set of option prices with different strike prices on that security. The risk-neutral density moments can be reflected in terms of quadratic, cubic and quartic payoffs. In particular, Bakshi, Kapadia and Madan (2003) show that the τ-maturity price of a security that pays the quadratic, cubic and quartic return on the base security can be expressed as

$$V(t,\tau) = \int_{S(t)}^{\infty} \frac{2\left(1-\ln\left(\frac{K}{S(t)}\right)\right)}{K^2} C(t,\tau;K)dK + \int_{0}^{S(t)} \frac{2\left(1+\ln\left(\frac{S(t)}{K}\right)\right)}{K^2} P(t,\tau;K)dK \quad (2)$$

$$W(t,\tau) = \int_{S(t)}^{\infty} \frac{6\ln\left(\frac{K}{S(t)}\right)-3\left(\ln\left(\frac{K}{S(t)}\right)\right)^2}{K^2} C(t,\tau;K)dK + \int_{0}^{S(t)} \frac{6\ln\left(\frac{S(t)}{K}\right)+3\left(\ln\left(\frac{S(t)}{K}\right)\right)^2}{K^2} P(t,\tau;K)dK \quad (3)$$

$$X(t,\tau) = \int_{S(t)}^{\infty} \frac{12\ln\left(\frac{K}{S(t)}\right)^2 - 4(\ln(\frac{K}{S(t)}))^3}{K^2} C(t,\tau;K)dK + \int_{0}^{S(t)} \frac{12\ln\left(\frac{S(t)}{K}\right)^2 + 3\,(\ln(\frac{S(t)}{K}))^3}{K^2} P(t,\tau;K)dK \quad (4)$$

where $V(t,\tau)$, $W(t,\tau)$ and $X(t,\tau)$ are the quadratic, cubic and quartic contracts, respectively, and $C(t,\tau;K)$ and $P(t,\tau;K)$ are the prices of call and put options written on the underlying stock with strike price K and expiration τ periods from time *t*. As can be seen, the procedure involves using a weighted sum of out-of-the-money options across varying strike prices to construct the prices of payoffs related to the second, third and fourth moments of returns. Given the prices of these contracts, risk-neutral moments can be calculated as

$$\sigma_Q^2 = e^{r\tau}V(t,\tau) - \mu(t,\tau)^2$$

$$SKEW_Q = \frac{e^{r\tau}W(t,\tau) - 3e^{r\tau}\mu(t,\tau)V(t,\tau) + 2\mu(t,\tau)^3}{(e^{r\tau}V(t,\tau) - \mu(t,\tau)^2)^{3/2}}$$

$$KURT_Q = \frac{e^{r\tau}X(t,\tau) - 4e^{r\tau}W(t,\tau) + 6e^{r\tau}V(t,\tau) - 3\mu(t,\tau)^4}{(e^{r\tau}V(t,\tau) - \mu(t,\tau)^2)^2}$$

where $\mu(t,\tau) = e^{r\tau}(1 - e^{-r\tau} - \frac{1}{2}V(t,\tau) - \frac{1}{6}W(t,\tau) - \frac{1}{24}X(t,\tau)$ and *r* is the risk-free rate. These integrals and risk-neutral moments are calculated separately for each maturity on a given day. Based on the risk-neutral skewness estimates for each maturity, I calculate four different measures of risk-neutral skewness measures. *RSKEWVOL* and *RSKEWOPEN* weight each maturity-specific risk-neutral skewness estimate by the total volume and total open interest of the options used to calculate the estimates, respectively. *RSKEWEQ* weights each risk-neutral skewness estimate for each maturity equally. *RSKEWMO* is the risk-neutral skewness measure that is derived from options whose maturity is closest to thirty days on a given day. The descriptive statistics associated with each risk-neutral skewness measure presented in Panel C of Table 1. The mean risk-neutral skewness is around -3 and the median risk neutral skewness is around -2.5 which are about the same as the standard deviation in absolute magnitude. One can see that risk-neutral skewness measures can get highly negative indicated by the minimum values and kurtosis of risk-neutral skewness measures. Finally, all four risk-neutral skewness measures have left-skewed distributions.

Table 4 presents results from the time-series regressions of the excess market returns on the risk-neutral skewness measures, conditional volatility and macroeconomic control variables. The dependent variable in the first set of regression results is one-day ahead excess market returns. None of the risk-neutral skewness measures have significant coefficients and the *t*-statistics range between 1.08 and 1.23. This result remains intact for longer horizons over which expected market returns are measured. In all of the specifications, all four risk-neutral skewness measures have insignificant coefficients. In this table, the control for the conditional variance is *RVAR*, the risk-neutral variance measures derived using the equations in Bakshi, Kapadia and Madan (2003). If the specification includes *RSKEWVOL*, then the risk-neutral variance control is based on weighting maturity-specific risk-neutral variance measures by total option volumes. Similarly, the risk-neutral variance is calculated differently for each specification using the same procedure as in the calculation of the particular risk-neutral skewness measure used in the specification. The coefficient on *RVAR* is significantly positive in all of the specifications for all return measurement horizons. The lowest *t*-statistic associated with the coefficients of risk-neutral variances is 2.03 whereas the highest *t*-statistic is 4.35. The detrended riskless rate and the dividend-price ratio are positively and significantly related to expected aggregate returns.

3.4 Consumer Sentiment Index

To lend more support to the idea that the predictive ability of volatility spreads on expected market returns is due to the information flow from option markets to stock markets, I focus on the announcements of consumer sentiment index. This index is compiled by University of Michigan through a nationally representative survey based on telephonic household interviews and published monthly. The data is available for download from the Federal Reserve statistical release website. Lemmon and Portniaguina (2006) analyze the relation between the consumer sentiment index and asset prices and find that there is a statistically significant link between the two variables. If volatility spreads contain information about the consumer sentiment index, then one would expect the intertemporal relation between volatility spreads and expected market returns to be stronger when the consumer sentiment index is particularly high or low. I estimate the following regression model to test this hypothesis.

$$R_{t+1} = \alpha + \gamma \cdot E_t[VAR_{t+1}] + \beta_1 \cdot VSPLUS_t + \beta_2 \cdot VSMINUS_t + \theta \cdot X_t + \varepsilon_{t+1} \qquad (5)$$

where $VSPLUS_t$ is equal to the volatility spread if the consumer sentiment index is greater than its 90th percentile or less than its 10th percentile over the sample period, and 0 otherwise; and $VSMINUS_t$ is equal to the volatility spread if the consumer sentiment index is less than its 90th percentile and greater than its 10th percentile over the sample period, and 0 otherwise.[15] If the information in volatility spreads related to consumer sentiment is instrumental in the predictive power of the volatility spreads on expected market returns, then β_1 is expected to be more negative than β_2.

[15] The results are qualitatively similar if the extreme levels of the consumer sentiment index are defined based on the 25th and 75th percentiles.

Table 5 presents the empirical results. The last column presents the p-values associated with the Wald test for the equality of the coefficients of $VSPLUS$ and $VSMINUS$. I find that for all horizons from one week to one month and for all four volatility spread measures, the coefficient of $VSPLUS$ is significantly more negative than $VSMINUS$. For example, for the one-day horizon, when the highest open interest volatility spread measure is used in the empirical specification, the coefficient of $VSPLUS$ is -0.0290 with a t-statistic of -4.17 and the coefficient of $VSMINUS$ is -0.0154 with a t-statistic of -3.44. The p-value associated with the equality of these two coefficients is 0.0229 confirming the conjecture that the predictive ability of volatility spreads on expected market returns is at least partially driven by the information embedded in volatility spreads related to consumer sentiment. The same pattern holds for all coefficient pairs up to an expected return horizon of one month. The p-values associated with the Wald tests for the equality of the coefficients of $VSPLUS$ and $VSMINUS$ range between 0.0077 and 0.0459.

4. Robustness Checks

4.1. Accounting for Non-Normalities in the Empirical Return Distribution

There is substantial empirical evidence showing that the distribution of stock returns is typically skewed to the left, is peaked around the mode (leptokurtic) and has fat tails. The fat tails and negative skewness suggest that extreme outcomes happen much more frequently than would be predicted by the normal distribution, and the negative returns of a given magnitude have higher probabilities than positive returns of the same magnitude. This also suggests that the normality assumption in estimating the intertemporal relation between risk-neutral volatility spreads and expected returns based on the OLS can produce parameters that are inappropriate measures of the regression coefficients. To account for skewness and excess kurtosis in the data, I use the skewed t distribution of Hansen (1994):

$$f(z_t;\mu,\sigma,v,\lambda)=\begin{cases} bc\left(1+\frac{1}{v-2}\left(\frac{bz_t+a}{1-\lambda}\right)^2\right)^{-\frac{v+1}{2}} & \text{if } z_t<-a/b \\ bc\left(1+\frac{1}{v-2}\left(\frac{bz_t+a}{1+\lambda}\right)^2\right)^{-\frac{v+1}{2}} & \text{if } z_t\geq -a/b \end{cases} \tag{6}$$

where $z_t = \frac{R_t - \mu}{\sigma}$ is the standardized excess market return, the constants *a*, *b*, and *c* are given by

$$a = 4\lambda c\left(\frac{v-2}{v-1}\right), \quad b^2 = 1+3\lambda^2 - a^2, \quad c = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma\left(\frac{v}{2}\right)} \ . \tag{7}$$

Hansen (1994) shows that this density is defined for $2 < v < \infty$ and $-1 < \lambda < 1$. This density has a single mode at $-a/b$, which is of opposite sign with the parameter λ. Thus, if $\lambda > 0$, the mode of the density is to the left of zero and the variable is skewed to the right, and vice versa when $\lambda < 0$. Furthermore, if $\lambda = 0$, Hansen's distribution reduces to the traditional standardized t distribution. If $\lambda = 0$ and $v = \infty$, it reduces to a normal density.

I estimate the extended version of the ICAPM with control variables:

$$R_{t+1} = \alpha + \gamma \cdot VIXSQ_t + \beta \cdot VS_t + \theta \cdot X_t + \varepsilon_{t+1} \tag{8}$$

where the intercept (α) and slope coefficients (γ, β, θ) as well as the standard deviation, skewness, and tail-thickness parameters of the Skewed t density (σ, λ, v) are estimated simultaneously by maximizing the conditional log-likelihood function of R_{t+1},

$$LnL = n\ln b + n\ln\Gamma\left(\frac{v+1}{2}\right) - \frac{n}{2}\ln\pi - n\ln\Gamma(v-2) - n\ln\Gamma\left(\frac{n}{2}\right) - n\ln\sigma - \left(\frac{v+1}{2}\right)\sum_{t=1}^{n}\ln\left(1+\frac{d_t^2}{(v-2)}\right) \quad (9)$$

where $d_t = \frac{bz_t + a}{(1-\lambda s)}$ and s is a sign dummy taking the value of 1 if $bz_t + a < 0$ and $s = -1$ otherwise.

Table 6 presents the maximum likelihood parameter estimates along with the corresponding p-values in parentheses. When the volatility spread measures are included in the estimation along with VIXSQ and macroeconomic controls, I find that all volatility spread measures have significantly negative coefficients. For the one-day horizon, the lowest (highest) volatility spread coefficient (in absolute magnitude) is associated with HVVS (OWVS) and is equal to -0.0116 (-0.0313). Without any exception, all volatility spread coefficients are significant at the 0.5% level or better. The significantly negative coefficients associated with the volatility spreads remain intact up to the one-month return horizon. For the one-month horizon, the lowest (highest) volatility spread coefficient (in absolute magnitude) is again associated with HVVS (OWVS) and is equal to -0.0838 (-0.1883). All the volatility spread coefficients are highly significant.

In all specifications, VIXSQ has a significantly positive coefficient confirming the positive intertemporal relation between conditional volatility and expected market returns. There is no significant relation between expected returns and the default and term premia, with the exception of the two-week ahead return specifications. The detrended riskless rate and the dividend yield are positively related to excess market returns for various horizons. Another notable point in Table 6 is that the tail-thickness parameter (v) is significantly greater than 2 and the null hypothesis of $1/v=0$ is strongly rejected. Moreover, the skewness parameter (λ) is positive and highly significant, indicating positive skewness and fat tails in the empirical distribution of daily returns. To summarize, after taking the non-normality of market returns and relatively infrequent events into account, the negative and significant link between the volatility spreads and the excess market returns remains intact.

4.2. Small Sample Biases

As argued by Stambaugh (1999), there exists a small sample bias in predictive regressions of the sort used in this study, because the regression disturbances are correlated with the regressors' innovations, hence the expectation of the regression disturbance conditional on the future values of regressors no longer equals zero. The small sample bias indicated by Stambaugh (1999) is a function of the bias of the autoregressive coefficients of the independent variables, the correlation between the error terms, and the sample size. The sign of the bias depends on the sign of the correlation between the error terms. If the regression disturbance is positively (negatively) correlated with the regressor's innovation, there is a negative (positive) bias.

Therefore, I consider the randomization technique of Nelson and Kim (1993) to correct for the small sample bias. I run each one of the predictive regressions, record the residuals, and estimate a first-order autoregression for the independent variables (in this case volatility spread measures, volatility proxies and macro-economic variables). The residuals of the first-order autoregression are randomized to create pseudo-independent variables and returns that have similar time-series properties as the actual series but have been generated under the null of no predictability. It should be noted that the pseudo stock return is generated as the unconditional mean plus the randomized error term and in each simulation, residuals from the predictive regression and the autoregressions for the independent variables are randomized simultaneously, hence the correlation that drives the Stambaugh bias is preserved. I repeat this randomization procedure 1000 times for each regression and create the empirical distribution of the coefficient estimates. Subsequently, the small sample bias adjusted coefficient estimates and *p*-values are estimated. Small sample bias adjusted *p*-values are computed as the percentage of times the simulated *t*-statistics are higher than the sample *t*-statistics. Both *t*-statistics are computed using the Newey-West (1987) correction for heteroscedasticity and autocorrelation. For example, *p*-value of 0.995 (0.005) shows that the coefficient is negative (positive) and significant at the 1% level.

As shown in Table 7, the skewness preference parameters are not affected by small sample bias. The magnitude and statistical significance of the coefficient estimates on the volatility spreads are almost the same as those reported in Table 2, indicating the existence of information flow from option markets to stock markets. For some of the specifications, the economic and statistical significance of the risk aversion coefficients and the slopes on control variables are slightly affected by the small sample bias correction.

4.3. Subsample Analysis

Guo (2006) highlights the importance of taking the time-varying nature of risk aversion into account in explaining asset returns. Similarly, it is possible that the coefficients associated with volatility spreads are also time-varying. Thus, I estimate the dependence of expected returns on the lagged volatility spreads using rolling regressions. Doing so also makes it possible to see whether the results hold in different sample periods. In the rolling regressions, I use the implied variance to control for conditional volatility[16] and also include the macroeconomic variables in the specification. To conserve space, only the results for OWVS are presented and the inferences are the same for the other measures of risk-neutral skewness.

For the one-day ahead return horizon, the rolling window is set to be about half of the entire sample period. The first 1,595 daily observations of excess returns on the S&P 500 index and the lagged volatility spreads are used to estimate the first volatility spread coefficient. Then, the sample is rolled forward by removing the first observation of the sample and adding one to the end, and another coefficient is estimated. This recursive estimation procedure is repeated until September 10, 2008. Figure 1 plots the estimated volatility spread coefficients and their associated *t*-statistics over time when one-day ahead returns are regressed on OWVS and the control variables. The coefficients associated with volatility spreads are always negative and the *t*-statistics are almost always greater than 2 in absolute magnitude. I also present descriptive statistics for the plotted coefficients. I find that the mean volatility spread coefficient is equal to -0.04321 and it is about nine times the standard deviation which equals 0.00476.

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[16] The results from the rolling regressions are qualitatively similar if the implied variance is replaced by the realized or range variance.

Figures 2 through 4 present the estimated volatility spread coefficients and their *t*-statistics over time for return horizons ranging from one-week to one-month. As can be seen, the volatility spread coefficients are always negative for the specifications where the dependent variable is either one-week, two-week or one-month ahead excess returns. Although the *t*-statistics are occasionally higher than -2, the frequency of *t*-statistics that are less than -2 is at least 80%. The mean volatility spread coefficients are at least 6.5 times the standard deviations. The results for the three-month horizon are presented in Figure 5. The coefficients associated with volatility spreads become positive for some subsamples and the frequency of *t*-statistics that are less than -2 is only 20%. These findings are consistent with those in Table 2.

The results from the rolling regressions clearly show that the relation between volatility spreads and expected market returns is robust over time, i.e., it is almost always negative throughout the sample period and statistically significant. The existence of information flow from option markets to stock market seems to be a stable phenomenon.

5. Conclusion

Demand-based option pricing models suggest that the demand for an option affects its expensiveness, which can be proxied by the implied volatility of the option. If put options attract more demand than call options, one would expect the implied volatilities of put options to become higher with respect to those of call options. If some traders demand more put (call) options before negative (positive) price movements due to their private information, then one would expect to see a significantly negative intertemporal relation between put minus call volatility spreads and returns of the underlying assets. In this study, I focus on the intertemporal relation between volatility spreads and returns at the aggregate level and find that volatility spreads are significantly and negatively related to excess market returns after controlling for various measures of conditional variance and different macroeconomic variables that proxy for the changes in future investment opportunities. As a by-product of the analysis, I find evidence for a significantly positive link between conditional variance and expected returns. This confirms the findings of some prior studies that uncover significantly positive relative risk aversion parameters. Rolling regressions indicate that the volatility spread-return relation is robust over time. Accounting for small sample biases and non-normalities in the return distribution do not alter the findings.

Since the volatility spread between out-of-the-money put options and at-the-money call options (i.e. the slope of the volatility smile) has been proposed as a measure of skewness by Xing, Zhang and Zhao (2009), I construct direct physical and risk-neutral skewness measures to make sure that the relation between volatility spreads and expected market returns is driven by information rather than skewness. The results indicate that there is no significant relation between various measures of skewness and expected market returns. To provide extra evidence for the informational role of option markets, I condition the relation between volatility spreads and excess market returns on the level of consumer sentiment index since prior research establishes a significant link between consumer sentiment and asset returns. The predictive ability of volatility spreads is stronger when consumer sentiment index is unusually high or low.

Table 1. Descriptive Statistics

This table presents descriptive statistics for various daily volatility spread and skewness measures. Panel A presents results for volatility spreads. HOVS (HVVS) is the implied volatility difference between the OTM put option and the ATM call option that have the highest open interest (volume) in a given trading day. OWVS (VWVS) is the difference between open interest-weighted (volume-weighted) average implied volatility of all OTM put options and open interest-weighted (volume-weighted) average implied volatility of all ATM call options. Panel B presents results for physical skewness measures. PSKEW1M is the daily physical skewness measure calculated as the skewness of the daily index returns over the past month. PSKEW3M is the daily physical skewness measure calculated as the skewness of the daily index returns over the past three months. PSKEW6M is the daily physical skewness measure calculated as the skewness of the daily index returns over the past six months. PSKEW12M is the daily physical skewness measure calculated as the skewness of the daily index returns over the past twelve months. Panel C presents results for risk-neutral skewness measures. RKEWVOL (RSKEWOPEN) is calculated according to Bakshi, Kapadia and Madan (2003) by weighting options by their total volumes (open interests). RSKEWEQ is calculated by equal-weighting options that correspond to the same time to expiration within the same day. RSKEWMO is calculated by using options whose time to expiration is closest to 30 days.

Panel A. Volatility Spreads

	Mean	Median	Std. dev.	Min	P25	P75	Max	Skewness	Kurtosis
HOVS	0.08296	0.07827	0.04435	-0.04150	0.05174	0.10744	0.38952	0.79660	4.58530
HVVS	0.08566	0.07840	0.04279	-0.05347	0.05537	0.10856	0.32271	1.06390	5.09077
OWVS	0.09467	0.09245	0.02533	0.00747	0.07788	0.10975	0.23195	0.52421	4.02377
VWVS	0.08907	0.08759	0.02664	-0.00214	0.07131	0.10437	0.21454	0.55795	4.28465

Panel B. Physical Skewness

	Mean	Median	Std. dev.	Min	P25	P75	Max	Skewness	Kurtosis
PSKEW1M	-0.01419	-0.00632	0.55449	-3.13123	-0.36492	0.31761	1.78629	-0.30797	4.50587
PSKEW3M	-0.07951	-0.07229	0.46049	-2.83421	-0.28289	0.18564	1.01381	-1.01749	6.38988
PSKEW6M	-0.12019	-0.06637	0.44307	-2.11497	-0.30608	0.15495	0.78256	-1.05268	4.85608
PSKEW12M	-0.13094	-0.05975	0.35260	-1.27074	-0.42991	0.10260	0.55136	-0.34617	2.39383

Panel C. Risk-Neutral Skewness

	Mean	Median	Std. dev.	Min	P25	P75	Max	Skewness	Kurtosis
RSKEWVOL	-3.1948	-2.5128	2.6027	-33.570	-3.5013	-1.8519	0.1435	-3.99541	26.86656
RSKEWOPEN	-3.1708	-2.4848	2.7128	-35.967	-3.4547	-1.8347	0.2212	-4.59705	35.14926
RSKEWEQ	-3.0334	-2.4615	2.2363	-33.570	-3.3510	-1.8482	-0.4182	-4.07337	30.80395
RSKEWMO	-3.1299	-2.4972	2.5363	-36.938	-3.44443	-1.8229	0.1503	-4.37393	34.63668

Table 2. Volatility Spreads and Market Returns

This table presents results from the regressions of the excess return of the S&P 500 index on volatility spreads, implied variance and macroeconomic variables. Volatility spread measures are defined in Table 1. VIXSQ is the implied variance which measures the market's forecast of the volatility of the S&P 500 index. Macroeconomic controls include RET, DEF, TERM, RREL and DP. RET is the lagged excess S&P 500 index return. DEF is the change in the default spread calculated as the change in the difference between the yields of BAA- and AAA-rated corporate bonds. TERM is the change in the term spread calculated as the change in the difference between the yields on the 10-year Treasury bond and the 1-month Treasury bill. RREL is the detrended riskless rate defined as the 1-month Treasury bill rate minus its 1-year backward moving average. DP is the aggregate dividend price ratio obtained by using the S&P 500 index return with and without dividends. Volatility spreads, VIXSQ, RREL and DP are measured at the end of the period before returns begin to accumulate. RET, DEF and TERM are measured over the period before returns begin to accumulate. In each regression, the dependent variable is the 1-day, 1-week, 2-week, 1-month or 3-month ahead excess market returns. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West (1987) adjusted *t*-statistics.

	Constant	HOVS	HVVS	OWVS	VWVS	VIXSQ	RET	DEF	TERM	RREL	DP
1-day	-0.0021	-0.0169				7.0803	0.0156	-3.7391	0.0395	0.1089	0.1537
	(-1.51)	(-3.80)				(2.47)	(0.79)	(-1.17)	(0.08)	(1.78)	(2.33)
	-0.0022		-0.0136			6.6450	0.0160	-3.6743	0.0871	0.0961	0.1512
	(-1.61)		(-2.98)			(2.28)	(0.81)	(-1.16)	(0.12)	(1.57)	(2.27)
	0.0002			-0.0363		7.1197	0.0146	-3.4869	0.0259	0.1120	0.1370
	(0.12)			(-4.33)		(2.47)	(0.74)	(-1.11)	(0.15)	(1.80)	(2.06)
	-0.0008				-0.0309	7.3331	0.0147	-3.6044	0.0796	0.1043	0.1505
	(-0.52)				(-3.91)	(2.49)	(0.75)	(-1.15)	(0.19)	(1.68)	(2.25)
1-week	-0.0104	-0.0515				5.7880	-0.0408	0.0653	1.5492	0.5947	0.6744
	(-1.72)	(-3.25)				(2.45)	(-1.15)	(0.01)	(1.60)	(2.19)	(2.32)
	-0.0122		-0.0235			5.4223	-0.0380	-0.0206	1.6520	0.5533	0.6650
	(-2.03)		(-1.85)			(2.26)	(-1.07)	(-0.01)	(1.66)	(2.03)	(2.27)
	-0.0043			-0.1006		5.7696	-0.0398	0.7353	1.6116	0.6033	0.6256
	(-0.67)			(-3.34)		(2.45)	(-1.13)	(0.16)	(1.66)	(2.20)	(2.16)
	-0.0088				-0.0635	5.7390	-0.0384	-0.2406	1.6535	0.5725	0.6643
	(-1.44)				(-2.43)	(2.39)	(-1.08)	(0.05)	(1.67)	(2.09)	(2.27)
2-week	-0.0250	-0.0622				5.9921	0.0570	6.9069	2.5771	1.5058	1.3571
	(-2.31)	(-2.48)				(3.04)	(1.21)	(1.22)	(2.56)	(2.84)	(2.60)
	-0.0262		-0.0435			5.8704	0.0629	6.9770	2.6420	1.4706	1.3572
	(-2.42)		(-2.30)			(2.93)	(1.35)	(1.22)	(2.58)	(2.77)	(2.59)
	-0.0165			-0.1324		5.9914	0.0571	7.9022	2.5856	1.5201	1.2924
	(-1.44)			(-2.79)		(3.06)	(1.23)	(1.40)	(2.54)	(2.85)	(2.49)
	-0.0229				-0.0806	6.0100	0.0617	7.1005	2.6433	1.4854	1.3493
	(-2.04)				(-1.97)	(3.03)	(1.32)	(1.25)	(2.58)	(2.79)	(2.58)
1-month	-0.0523	-0.0994				5.9616	0.0426	6.0332	2.2175	3.4446	2.6916
	(-2.20)	(-2.24)				(3.09)	(0.54)	(0.76)	(1.63)	(3.03)	(2.45)
	-0.0536		-0.0817			5.9069	0.0503	6.1776	2.2280	3.3885	2.7036
	(-2.25)		(-2.55)			(3.06)	(0.64)	(0.79)	(1.62)	(2.98)	(2.47)
	-0.0402			-0.1951		5.9109	0.0419	7.5690	2.1911	3.4498	2.5901
	(-1.58)			(-2.27)		(3.10)	(0.53)	(0.94)	(1.60)	(3.01)	(2.37)
	-0.0474				-0.1483	6.0035	0.0475	6.4178	2.1960	3.4008	2.6832
	(-1.91)				(-1.96)	(3.12)	(0.60)	(0.82)	(1.60)	(2.98)	(2.45)
3-month	-0.1450	-0.0137				4.6346	0.0387	12.7801	0.9620	8.8398	6.8185
	(-3.06)	(-0.16)				(4.09)	(0.38)	(1.16)	(0.33)	(2.66)	(2.75)
	-0.1389		-0.0910			4.6699	0.0362	13.1630	1.0320	8.9360	6.8359
	(-2.88)		(-1.26)			(4.14)	(0.35)	(1.21)	(0.35)	(2.70)	(2.78)
	-0.1235			-0.2197		4.6669	0.0284	14.0415	1.0911	9.0835	6.7064
	(-2.77)			(-1.24)		(4.12)	(0.28)	(1.28)	(0.37)	(2.72)	(2.80)
	-0.1273				-0.2181	4.7230	0.0302	13.8142	1.1135	9.0589	6.8078
	(-2.69)				(-1.28)	(4.13)	(0.29)	(1.27)	(0.38)	(2.72)	(2.80)

Table 3. Physical Skewness and Market Returns

This table presents results from the regressions of the excess return of the S&P 500 index on various measures of physical skewness, realized variance and macroeconomic variables. Physical skewness measures are defined in Table 1. Macroeconomic controls are defined in Table 2. REALVAR is the realized variance calculated as the sum of squared five-minute returns adjusted for the firs-order autocorrelation. Physical skewness, REALVAR, RREL and DP are measured at the end of the period before returns begin to accumulate. RET, DEF and TERM are measured over the period before returns begin to accumulate. In each regression, the dependent variable is the 1-day, 1-week, 2-week, 1-month or 3-month ahead excess market returns. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted *t*-statistics.

Constant	PSKEW1M	PSKEW3M	PSKEW6M	PSKEW12M	REALVAR	RET	DEF	TERM	RREL	DP
1-day										
-0.0019	0.00004				5.2356	0.0120	-3.8846	0.0003	0.0397	0.1088
(-1.78)	(0.11)				(2.41)	(0.58)	(-1.20)	(0.14)	(0.72)	(1.76)
-0.0018		-0.0005			5.3052	0.0125	-3.9978	0.0541	0.0377	0.0960
(-1.61)		(-1.11)			(2.48)	(0.61)	(-1.23)	(0.13)	(0.69)	(1.52)
-0.0019			-0.0004		5.3219	0.0124	-3.9601	0.0616	0.0396	0.1002
(-1.71)			(-0.90)		(2.49)	(0.61)	(-1.22)	(0.15)	(0.72)	(1.61)
-0.0020				0.0001	5.2351	0.0120	-3.8778	0.0607	0.0403	0.1101
(-1.79)				(0.21)	(2.42)	(0.58)	(-1.19)	(0.15)	(0.73)	(1.76)
1-week										
-0.0085	0.0001				4.3076	-0.0379	0.2315	1.7235	0.3328	0.5071
(-1.81)	(0.48)				(3.01)	(-1.06)	(0.05)	(1.73)	(1.34)	(1.91)
-0.0076		-0.0025			4.4089	-0.0341	-0.2165	1.7034	0.3216	0.4351
(-1.59)		(1.41)			(3.10)	(-0.97)	(-0.05)	(1.72)	(1.30)	(1.59)
-0.0080			-0.0015		4.3942	-0.0349	-0.0193	1.7308	0.3334	0.4644
(-1.71)			(-0.81)		(3.11)	(-0.99)	(-0.01)	(1.75)	(1.34)	(1.72)
-0.0085				0.0013	4.3108	-0.0369	0.2819	1.7274	0.3393	0.5141
(-1.80)				(0.46)	(3.01)	(-1.05)	(0.06)	(1.74)	(1.37)	(1.90)
2-week										
-0.0165	0.0008				4.1399	0.0540	7.3722	2.6721	0.9685	0.9728
(-1.96)	(0.29)				(3.94)	(1.11)	(1.29)	(2.45)	(1.97)	(2.04)
-0.0147		-0.0055			4.2528	0.0591	6.9866	2.6456	0.9439	0.8361
(-1.73)		(-1.64)			(4.05)	(1.25)	(1.20)	(2.44)	(1.94)	(1.70)
-0.0158			-0.0027		4.2173	0.0567	7.0592	2.6893	0.9709	0.9087
(-1.89)			(-0.77)		(4.02)	(1.19)	(1.21)	(2.48)	(1.98)	(1.88)
-0.0165				0.0021	4.1405	0.0543	7.4922	2.6799	0.9794	0.9927
(-1.97)				(0.42)	(3.93)	(1.13)	(1.31)	(2.44)	(2.00)	(2.05)
1-month										
-0.0267	-0.0022				3.2421	0.0083	6.2420	1.6476	2.0994	1.6785
(1.53)	(-0.45)				(3.52)	(0.12)	(0.79)	(1.14)	(1.96)	(1.71)
-0.0239		-0.0120			3.3107	0.0067	5.6572	1.4866	1.9944	1.4488
(-1.36)		(-1.72)			(3.46)	(0.10)	(0.73)	(1.05)	(1.92)	(1.44)
-0.0264			-0.0048		3.2855	0.0042	5.6957	1.6682	2.0970	1.6238
(-1.53)			(-0.66)		(3.54)	(0.06)	(0.72)	(1.17)	(1.97)	(1.65)
-0.0280				0.0048	3.2245	0.0025	6.5829	1.6657	2.1203	1.7974
(-1.61)				(0.48)	(3.56)	(0.04)	(0.83)	(1.15)	(1.98)	(1.81)
3-month										
-0.0402	-0.0158				1.1341	-0.1090	13.9853	-2.4944	4.4591	3.4166
(-0.98)	(-1.67)				(2.02)	(-1.21)	(1.07)	(-0.92)	(1.39)	(1.43)
-0.0398		-0.0222			1.2231	-0.1050	13.2932	-2.6970	4.1969	3.2664
(-0.98)		(-1.31)			(2.26)	(-1.18)	(1.00)	(-1.00)	(1.35)	(1.35)
-0.0439			-0.0040		1.1991	-0.1106	13.4612	-2.1782	4.6322	3.5979
(-1.05)			(-0.24)		(2.12)	(-1.18)	(1.05)	(-0.77)	(1.41)	(1.44)
-0.0494				0.0256	1.2052	-0.1110	15.7656	-1.9475	4.9131	4.1715
(-1.16)				(0.97)	(2.04)	(-1.21)	(1.31)	(-0.68)	(1.48)	(1.62)

Table 4. Risk-Neutral Skewness and Market Returns

This table presents results from the regressions of the excess return of the S&P 500 index on various measures of risk-neutral skewness, risk-neutral variance and macroeconomic variables. Risk-neutral skewness measures are defined in Table 1. Macroeconomic controls are defined in Table 2. RVAR is the risk-neutral variance and is calculated differently for each specification using the same procedure as in the calculation of the particular risk-neutral skewness measure included in the specification. Risk-neutral skewness, RVAR, RREL and DP are measured at the end of the period before returns begin to accumulate. RET, DEF and TERM are measured over the period before returns begin to accumulate. In each regression, the dependent variable is the 1-day, 1-week, 2-week, 1-month or 3-month ahead excess market returns. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted *t*-statistics.

Constant	RSKEWVOL	RSKEWOP	RSKEWEQ	RSKEWMO	RVAR	RET	DEF	TERM	RREL	DP
1-day										
-0.0029	0.0001				0.2990	0.0160	-3.7389	0.0876	0.1072	0.1463
(-2.26)	(1.20)				(2.49)	(0.80)	(-1.16)	(0.14)	(1.74)	(2.27)
-0.0030		0.0001			0.2826	0.0156	-3.6968	0.0629	0.1010	0.1461
(-2.32)		(1.08)			(2.60)	(0.78)	(-1.15)	(0.11)	(1.68)	(2.29)
-0.0028			0.0001		0.2521	0.0155	-3.7781	0.0548	0.0958	0.1442
(-2.10)			(1.11)		(2.08)	(0.77)	(-1.17)	(0.13)	(1.55)	(2.22)
-0.0022				0.0001	0.2074	0.0138	-3.9465	0.0576	0.0818	0.1245
(1.75)				(1.23)	(2.03)	(0.69)	(-1.21)	(0.14)	(1.34)	(1.97)
1-week										
-0.0126	0.0003				0.2512	-0.0288	0.0741	1.6820	0.6101	0.6468
(-2.22)	(1.13)				(2.50)	(-1.07)	(0.02)	(1.70)	(2.24)	(2.29)
-0.0133		0.0002			0.2553	-0.0389	0.2955	1.6439	0.6096	0.6648
(-2.39)		(1.12)			(2.86)	(-1.07)	(0.06)	(1.67)	(2.29)	(2.38)
-0.0121			0.0003		0.2118	-0.0404	0.1141	1.6854	0.5695	0.6400
(-2.03)			(1.10)		(2.05)	(-1.10)	(0.02)	(1.69)	(2.07)	(2.24)
-0.0103				0.0003	0.2014	-0.0463	-0.3391	1.6305	0.5291	0.5769
(-1.89)				(1.14)	(2.11)	(-1.31)	(-0.07)	(1.63)	(1.97)	(2.08)
2-week										
-0.0227	0.0006				0.2169	0.0501	7.4134	2.5882	1.4544	1.2120
(-2.26)	(1.33)				(2.61)	(1.08)	(1.31)	(2.54)	(2.72)	(2.40)
-0.0243		0.0005			0.2264	0.0513	7.6776	2.5521	1.4646	1.2511
(-2.47)		(1.30)			(3.07)	(1.12)	(1.37)	(2.52)	(2.80)	(2.50)
-0.0224			0.0007		0.1920	0.0493	7.2349	2.6213	1.4205	1.2222
(-2.12)			(1.34)		(2.24)	(1.06)	(1.27)	(2.55)	(2.64)	(2.38)
-0.0190				0.0006	0.1811	0.0397	6.9826	2.5226	1.3193	1.0950
(-1.97)				(1.26)	(2.25)	(0.86)	(1.24)	(2.45)	(2.48)	(2.19)
1-month										
-0.0385	0.0021				0.1849	0.0233	7.3240	1.9706	3.3078	2.3088
(1.84)	(1.92)				(2.43)	(0.31)	(0.94)	(1.47)	(2.89)	(2.22)
-0.0402		0.0018			0.1834	0.0229	7.7684	1.8678	3.2385	2.3238
(-1.97)		(1.90)			(2.76)	(0.32)	(1.01)	(1.41)	(2.86)	(2.26)
-0.0388			0.0025		0.1719	0.0242	7.0971	2.0673	3.3269	2.3665
(-1.76)			(1.93)		(2.16)	(0.32)	(0.92)	(1.51)	(2.87)	(2.24)
-0.0306				0.0022	0.1509	0.0086	7.2270	1.8694	3.0659	2.0573
(-1.55)				(1.94)	(2.08)	(0.12)	(0.93)	(1.36)	(2.71)	(2.03)
3-month										
-0.0995	0.0025				0.1537	-0.0200	14.2936	0.1578	8.2407	5.6729
(-2.31)	(1.25)				(4.34)	(-0.21)	(1.30)	(0.05)	(2.47)	(2.38)
-0.0953		0.0023			0.1369	-0.0316	14.5082	-0.6522	7.9096	5.5507
(-2.21)		(1.29)			(4.26)	(-0.33)	(1.30)	(-0.02)	(2.39)	(2.33)
-0.1129			0.0030		0.1627	-0.0028	13.8870	0.6304	8.6339	6.1613
(-2.53)			(1.19)		(4.35)	(-0.03)	(1.27)	(0.22)	(2.58)	(2.57)
-0.0823				0.0026	0.1312	-0.0421	14.4946	-0.3201	7.5904	5.0993
(-1.99)				(1.35)	(4.25)	(-0.45)	(1.27)	(-0.11)	(2.30)	(2.16)

Table 5. Consumer Sentiment Index

This table presents results from the regressions of the excess return of the S&P 500 index on volatility spreads, VIXSQ and macroeconomic variables. I define a dummy variable equal to one if the consumer sentiment index is less than the 10^{th} percentile or greater than the 90^{th} percentile among the observed consumer sentiment values over the sample period. VSPLUS is equal to the value of the volatility spread if the dummy variable is equal to one and 0 otherwise. VSMINUS is equal to the value of the volatility spread if the dummy variable is equal to zero and 0 otherwise. Volatility spread measures are defined in Table 1. VIXSQ and macroeconomic controls are defined in Table 2. In each regression, the dependent variable is the 1-day, 1-week, 2-week, 1-month or 3-month ahead excess market returns. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted *t*-statistics. The final column presents p-values associated with the F-test for the equality of the coefficients of VSPLUS and VSMINUS.

	Constant	VSPLUS	VSMINUS	VIXSQ	RET	DEF	TERM	RREL	DP	p-value
1-day										
HOVS	-0.0022	-0.0290	-0.0154	7.5483	0.0154	-3.5297	0.0425	0.1135	0.1568	0.0229
	(-1.55)	(-4.17)	(-3.44)	(2.54)	(0.78)	(-1.10)	(0.11)	(1.87)	(2.38)	
HVVS	-0.0024	-0.0250	-0.0112	7.1315	0.0158	-3.5886	0.0412	0.094	0.159	0.0077
	(-1.74)	(-4.01)	(-2.42)	(2.37)	(0.80)	(-1.13)	(0.10)	(1.56)	(2.38)	
OWVS	0.0001	-0.0452	-0.0349	7.5277	0.0144	-3.398	0.0625	0.1122	0.1408	0.0459
	(0.06)	(-4.70)	(-4.14)	(2.53)	(0.74)	(-1.07)	(0.15)	(1.83)	(2.12)	
VWVS	-0.0009	-0.0414	-0.029	7.7905	0.0145	-3.5161	0.0731	0.1033	0.1562	0.0239
	(-0.61)	(-4.46)	(-3.65)	(2.56)	(0.74)	(-1.11)	(0.18)	(1.69)	(2.34)	
1-week										
HOVS	-0.0105	-0.1009	-0.0453	6.1062	-0.0443	0.8016	1.5171	0.6100	0.6794	0.0177
	(-1.73)	(-4.03)	(-2.79)	(2.52)	(-1.25)	(0.17)	(1.53)	(2.27)	(2.34)	
HVVS	-0.0129	-0.0640	-0.0150	5.7473	-0.0387	0.4486	1.6580	0.5476	0.6891	0.0160
	(-2.13)	(-2.98)	(-1.15)	(2.34)	(-1.10)	(0.10)	(1.65)	(2.04)	(2.35)	
OWVS	-0.0047	-0.1414	-0.0941	6.1211	-0.0408	1.2175	1.5935	0.6038	0.6386	0.0274
	(-0.72)	(-4.13)	(-3.09)	(2.53)	(-1.17)	(0.26)	(1.62)	(2.24)	(2.20)	
VWVS	-0.0094	-0.1065	-0.0556	6.0943	-0.0390	0.7217	1.6398	0.5687	0.6841	0.0219
	(-1.52)	(-3.34)	(-2.10)	(2.47)	(-1.11)	(0.15)	(1.64)	(2.11)	(2.34)	
2-week										
HOVS	-0.0248	-0.1392	-0.0532	6.1887	0.0501	7.9832	2.5128	1.5241	1.3496	0.0325
	(-2.28)	(-3.33)	(-2.05)	(3.06)	(1.08)	(1.44)	(2.49)	(2.92)	(2.59)	
HVVS	-0.0271	-0.1063	-0.0303	6.1001	0.0609	7.7769	2.6415	1.4630	1.3868	0.0352
	(-2.47)	(-2.95)	(-1.54)	(2.96)	(1.32)	(1.41)	(2.60)	(2.80)	(2.65)	
OWVS	-0.0168	-0.2032	-0.1221	6.2642	0.0544	8.9433	2.5638	1.5233	1.3032	0.0289
	(-1.45)	(-3.68)	(-2.54)	(3.10)	(1.18)	(1.64)	(2.54)	(2.91)	(2.52)	
VWVS	-0.0236	-0.1524	-0.0676	6.2762	0.0593	8.0841	2.6272	1.4809	1.3722	0.0285
	(-2.07)	(-2.95)	(-1.62)	(3.07)	(1.28)	(1.47)	(2.59)	(2.84)	(2.63)	
1-month										
HOVS	-0.0515	-0.1996	-0.0877	6.0454	0.0346	6.8163	2.1327	3.4567	2.6597	0.0409
	(-3.10)	(-3.48)	(-2.41)	(4.40)	(0.62)	(1.17)	(2.16)	(4.51)	(3.52)	
HVVS	-0.0541	-0.1711	-0.0633	6.0152	0.0449	7.0633	2.1791	3.3673	2.7152	0.0280
	(-3.27)	(-3.52)	(-2.28)	(4.34)	(0.80)	(1.23)	(2.20)	(4.39)	(3.60)	
OWVS	-0.0397	-0.3112	-0.1795	6.0740	0.0355	8.9688	2.1427	3.4553	2.5725	0.0090
	(-2.19)	(-4.26)	(-2.74)	(4.44)	(0.64)	(1.56)	(2.18)	(4.50)	(3.42)	
VWVS	-0.0476	-0.2637	-0.1283	6.1563	0.0415	7.7501	2.1431	3.3908	2.6837	0.0100
	(-2.75)	(-3.85)	(-2.27)	(4.47)	(0.74)	(1.36)	(2.17)	(4.43)	(3.57)	
3-month										
HOVS	-0.1433	-0.1089	-0.0034	4.6684	0.0356	13.2969	0.9911	8.9571	6.7289	0.4781
	(-2.96)	(-0.73)	(-0.04)	(4.13)	(0.34)	(1.21)	(0.35)	(2.76)	(2.68)	
HVVS	-0.1383	-0.2135	-0.0671	4.7250	0.0345	14.1640	1.0216	9.0138	6.7647	0.2644
	(-2.83)	(-1.63)	(-0.88)	(4.18)	(0.34)	(1.32)	(0.36)	(2.81)	(2.73)	
OWVS	-0.1211	-0.3621	-0.2014	4.7295	0.0248	15.2650	1.0853	9.2074	6.5732	0.2613
	(-2.65)	(-1.73)	(-1.12)	(4.17)	(0.24)	(1.41)	(0.38)	(2.85)	(2.70)	
VWVS	-0.1258	-0.3644	-0.1935	4.7867	0.0275	15.1010	1.0882	9.1562	6.7018	0.2464
	(-2.61)	(-1.71)	(-1.12)	(4.17)	(0.27)	(1.42)	(0.38)	(2.85)	(2.73)	

Table 6. Accounting for Non-Normalities in the Empirical Return Distribution

This table presents results from the regressions of the excess return of the S&P 500 index on volatility spreads, implied variance and macroeconomic variables. Volatility spread measures are defined in Table 1. VIXSQ and macroeconomic controls are defined in Table 2. Volatility spreads, VIXSQ, RREL and DP are measured at the end of the period before returns begin to accumulate. RET, DEF and TERM are measured over the period before returns begin to accumulate. The estimations are based on the Skewed t density of Hansen (1994). In each regression, the dependent variable is the 1-day, 1-week, 2-week, 1-month or 3-month ahead excess market returns. For each regression, the first row gives the intercepts, slope coefficients and parameter estimates for the Skewed t density. σ, *ν*, and *λ* represent the standard deviation, tail-thickness and skewness parameters, respectively. The second row presents Newey-West (1987) adjusted *t*-statistics for slope coefficients or *t*-statistics associated with the maximum likelihood parameter estimates.

	Constant	HOVS	HVVS	OWVS	VWVS	VIXSQ	RET	DEF	TERM	RREL	DP
1-day	-0.0007	-0.0147				9.3749	0.0052	-1.9259	0.2903	0.0889	0.1951
	(-0.56)	(-3.81)				(6.02)	(0.35)	(-0.77)	(0.93)	(1.74)	(3.52)
	-0.0005		-0.0116			8.7236	0.0057	-1.8801	0.3280	0.0747	0.1859
	(-0.45)		(-3.01)			(5.58)	(0.39)	(-0.75)	(1.05)	(1.46)	(3.41)
	0.0014			-0.0313		9.2438	0.0052	-1.9621	0.3285	0.0917	0.1796
	(1.01)			(-4.71)		(5.95)	(0.35)	(-0.78)	(1.05)	(1.79)	(3.24)
	0.0008				-0.0282	9.7741	0.0050	-1.8954	0.3630	0.0840	0.1932
	(0.61)				(-4.56)	(6.23)	(0.34)	(-0.76)	(1.16)	(1.64)	(3.48)
1-week	-0.0012	-0.0469				9.7092	-0.0539	-2.5624	0.5009	0.4625	0.8101
	(-0.44)	(-5.29)				(13.82)	(-3.55)	(-0.93)	(1.44)	(3.83)	(6.42)
	-0.0016		-0.0294			9.5046	-0.0516	-2.2909	0.5652	0.4312	0.7891
	(-0.57)		(-3.30)			(13.53)	(-3.39)	(-0.84)	(1.59)	(3.58)	(6.24)
	0.0046			-0.0880		9.7105	-0.0552	-1.8368	0.5634	0.4717	0.7562
	(1.45)			(-5.96)		(14.04)	(-3.63)	(-0.67)	(1.59)	(3.93)	(5.95)
	0.0013				-0.0639	9.8014	-0.0535	-2.2186	0.5954	0.4382	0.7964
	(0.41)				(-4.40)	(13.92)	(-3.52)	(-0.82)	(1.68)	(3.65)	(6.28)
2-week	-0.0138	-0.0543				8.0603	0.0464	6.0816	1.4961	1.2614	1.5098
	(-3.51)	(-4.52)				(17.57)	(2.93)	(2.53)	(4.28)	(7.03)	(8.71)
	-0.0140		-0.0454			8.0517	0.0511	6.4489	1.5300	1.2439	1.5072
	(-3.53)		(-3.69)			(17.60)	(3.22)	(2.68)	(4.40)	(6.97)	(8.70)
	-0.0045			-0.1240		8.1599	0.0415	7.1984	1.5337	1.2816	1.4626
	(-1.03)			(-6.00)		(18.02)	(2.62)	(2.97)	(4.41)	(7.17)	(8.43)
	-0.0105				-0.0808	8.1762	0.0480	6.5019	1.5414	1.2505	1.5073
	(-2.47)				(-4.11)	(17.77)	(3.03)	(2.69)	(4.42)	(6.99)	(8.68)
1-month	-0.0367	-0.0956				7.4795	0.0293	3.0334	1.6444	2.6733	2.9502
	(-4.11)	(-5.55)				(23.10)	(1.78)	(1.05)	(4.41)	(9.45)	(10.84)
	-0.0264		-0.0838			7.2990	0.0339	3.7903	1.6634	2.6367	2.8789
	(-4.03)		(-4.77)			(22.34)	(2.06)	(1.32)	(4.45)	(9.33)	(10.59)
	-0.0140			-0.1883		7.2329	0.0258	5.1156	1.6865	2.6655	2.8097
	(-1.92)			(-6.61)		(22.34)	(1.55)	(1.77)	(4.48)	(9.47)	(10.17)
	-0.0203				-0.1569	7.3623	0.0294	4.0389	1.6549	2.6263	2.9003
	(-2.88)				(-5.56)	(22.55)	(1.78)	(1.41)	(4.40)	(9.31)	(10.59)
3-month	-0.1497	-0.2317				5.4196	0.0150	12.7730	1.9680	0.1680	6.4500
	(-1.16)	(-0.44)				(2.17)	(0.07)	(0.25)	(0.17)	(1.58)	(1.35)
	-0.1301		-0.1440			5.2256	0.0051	20.5130	1.4714	0.1736	4.8667
	(-1.07)		(-0.64)			(1.89)	(0.03)	(0.43)	(0.14)	(1.85)	(1.16)
	-0.1653			0.0916		4.9435	0.0164	22.0621	1.3678	0.1640	5.3180
	(-1.31)			(0.14)		(1.84)	(0.08)	(0.45)	(0.13)	(1.67)	(1.31)
	-0.1549				-0.0207	5.1411	0.0262	19.6783	1.6028	0.1652	5.4205
	(-1.25)				(-0.05)	(1.84)	(0.13)	(0.40)	(0.14)	(1.66)	(1.29)

Table 7. Small Sample Biases

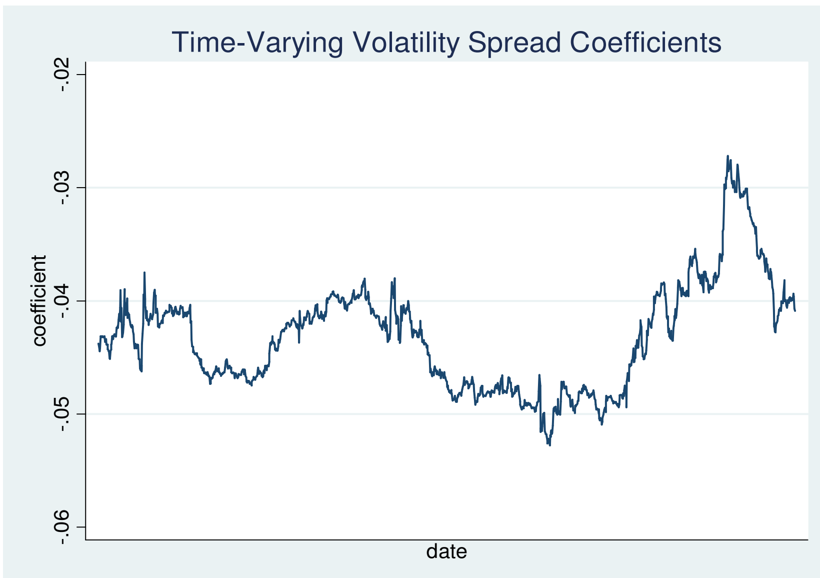
This table presents results from the regressions of the excess return of the S&P 500 index on volatility spreads, implied variance and macroeconomic variables. Volatility spread measures are defined in Table 1. VIXSQ and macroeconomic controls are defined in Table 2. Volatility spreads, VIXSQ, RREL and DP are measured at the end of the period before returns begin to accumulate. RET, DEF and TERM are measured over the period before returns begin to accumulate. In each regression, the dependent variable is the 1-day, 1-week, 2-week, 1-month or 3-month ahead excess market returns. The regressions employ the randomization method of Nelson and Kim (1993) to correct for small sample biases identified in Stambaugh (1999). For each regression, the first row gives the intercepts and slope coefficients. The second row presents the *p*-values associated with Newey-West (1987) adjusted *t*-statistics. A *p*-value of 0.995 (0.005) shows that the coefficient is negative (positive) at the 1% level.

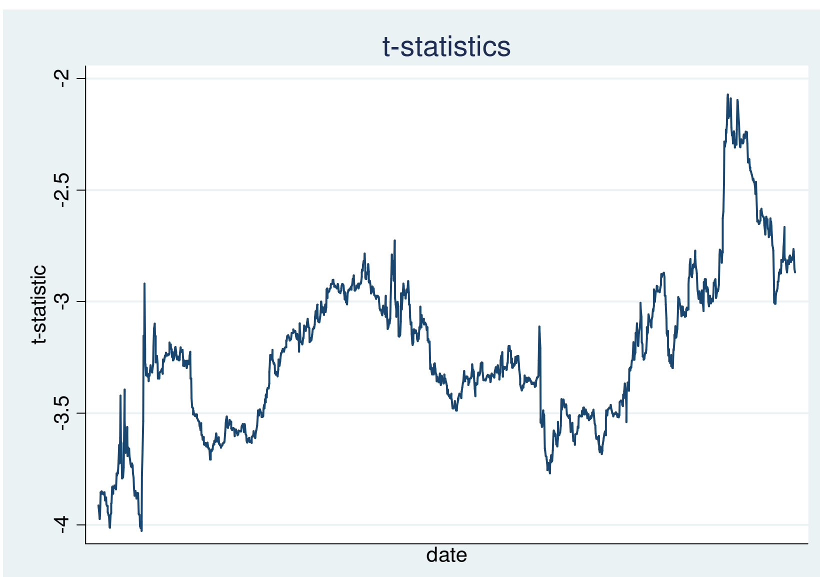
	Constant	HOVS	HVVS	OWVS	VWVS	VIXSQ	RET	DEF	TERM	RREL	DP
1-day	-0.001	-0.017				6.990	0.016	-3.640	0.026	0.107	0.090
	[0.862]	[1.000]				[0.010]	[0.231]	[0.868]	[0.460]	[0.050]	[0.051]
	-0.001		-0.014			6.442	0.015	-3.808	0.053	0.097	0.089
	[0.870]		[0.996]			[0.012]	[0.224]	[0.858]	[0.440]	[0.084]	[0.053]
	0.001			-0.036		6.963	0.014	-3.468	0.060	0.113	0.074
	[0.290]			[1.000]		[0.004]	[0.232]	[0.861]	[0.448]	[0.038]	[0.070]
	0.000				-0.031	7.044	0.014	-3.554	0.070	0.102	0.086
	[0.508]				[1.000]	[0.007]	[0.246]	[0.870]	[0.440]	[0.066]	[0.049]
1-week	-0.011	-0.052				5.746	-0.038	-0.282	1.543	0.593	0.622
	[0.969]	[0.999]				[0.007]	[0.834]	[0.535]	[0.068]	[0.015]	[0.031]
	-0.013		-0.024			5.348	-0.037	0.069	1.643	0.547	0.606
	[0.989]		[0.967]			[0.025]	[0.853]	[0.481]	[0.057]	[0.024]	[0.027]
	-0.005			-0.101		5.702	-0.038	0.712	1.629	0.609	0.564
	[0.796]			[0.999]		[0.008]	[0.848]	[0.432]	[0.043]	[0.012]	[0.032]
	-0.009				-0.064	5.717	-0.037	0.275	1.646	0.566	0.605
	[0.959]				[0.996]	[0.009]	[0.827]	[0.460]	[0.047]	[0.028]	[0.020]
2-week	-0.027	-0.063				5.967	0.059	7.011	2.582	1.516	1.307
	[1.000]	[0.997]				[0.000]	[0.079]	[0.086]	[0.001]	[0.002]	[0.002]
	-0.028		-0.044			5.835	0.065	6.958	2.658	1.481	1.306
	[1.000]		[0.991]			[0.000]	[0.057]	[0.103]	[0.005]	[0.001]	[0.003]
	-0.018			-0.135		5.984	0.060	7.818	2.615	1.520	1.232
	[0.973]			[0.999]		[0.003]	[0.062]	[0.078]	[0.002]	[0.000]	[0.004]
	-0.025				-0.082	5.982	0.064	7.215	2.633	1.496	1.300
	[0.997]				[0.991]	[0.000]	[0.053]	[0.088]	[0.006]	[0.003]	[0.003]
1-month	-0.058	-0.100				5.970	0.045	6.040	2.234	3.447	2.651
	[1.000]	[0.997]				[0.000]	[0.202]	[0.156]	[0.011]	[0.000]	[0.000]
	-0.059		-0.082			5.900	0.052	6.371	2.216	3.369	2.658
	[1.000]		[0.999]			[0.000]	[0.148]	[0.132]	[0.014]	[0.000]	[0.000]
	-0.045			-0.194		5.895	0.043	7.536	2.190	3.456	2.519
	[0.998]			[0.998]		[0.000]	[0.209]	[0.103]	[0.024]	[0.000]	[0.000]
	-0.052				-0.148	5.998	0.050	6.252	2.187	3.397	2.601
	[1.000]				[0.998]	[0.000]	[0.152]	[0.149]	[0.018]	[0.000]	[0.000]
3-month	-0.163	-0.015				4.650	0.041	12.854	0.944	8.818	6.747
	[1.000]	[0.563]				[0.000]	[0.340]	[0.127]	[0.397]	[0.013]	[0.020]
	-0.157		-0.094			4.663	0.038	13.223	1.039	8.960	6.817
	[1.000]		[0.890]			[0.000]	[0.350]	[0.100]	[0.340]	[0.020]	[0.007]
	-0.142			-0.218		4.674	0.031	14.011	1.121	9.099	6.648
	[1.000]			[0.903]		[0.000]	[0.370]	[0.110]	[0.333]	[0.003]	[0.000]
	-0.146				-0.214	4.723	0.032	13.736	1.094	9.076	6.764
	[1.000]				[0.890]	[0.000]	[0.370]	[0.140]	[0.390]	[0.010]	[0.010]

Figure 1. Time-Varying Volatility Spread Coefficients (Daily)

These figures present the coefficients of volatility spread (β) and their Newey-West (1987) adjusted *t*-statistics from the multivariate rolling regressions for the sample period of January 4, 1996 to September 10, 2008. The volatility spread is measured by OWVS as defined in Table 1. X_t includes the lagged excess return on the S&P 500 index and the lagged macrovariables (DEF, TERM, RREL, DP) defined in Table 2. The dependent variable is the one-day ahead excess market returns. The rolling window is set to be half the entire sample period and rolled forward one period for each regression:

$$R_{t+1} = \alpha + \gamma \cdot VIXSQ_t + \beta \cdot OWVS_t + \theta \cdot X_t + \varepsilon_{t+1}$$



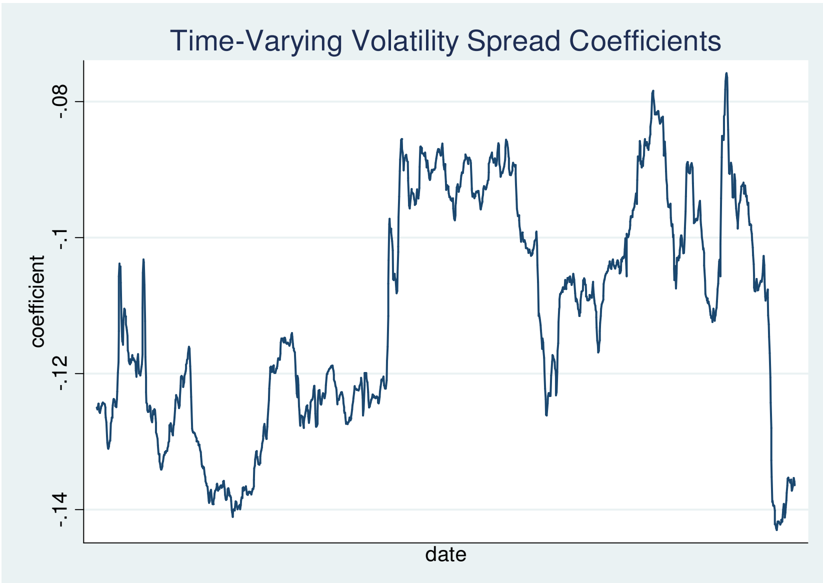


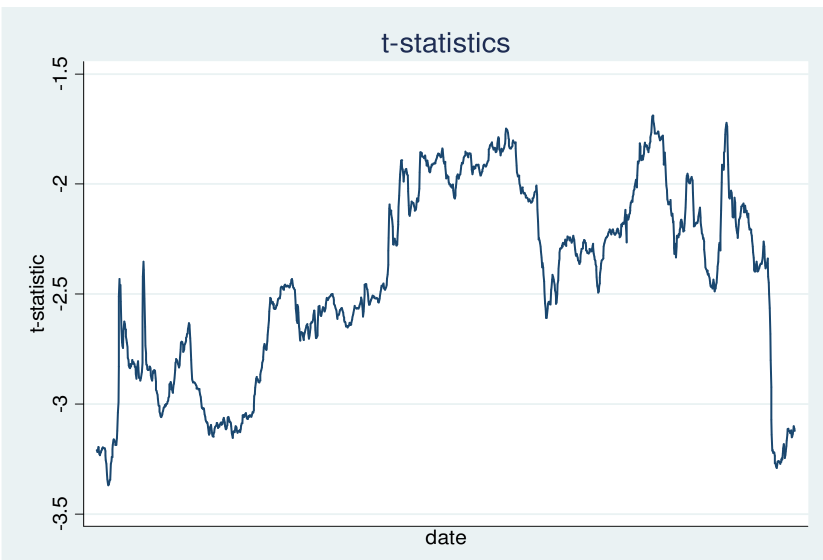
	Mean	Median	Std. Dev.	Min	Max
β	-0.04321	-0.04310	0.00476	-0.05281	-0.02719

Figure 2. Time-Varying Volatility Spread Coefficients (Weekly)

These figures present the coefficients of volatility spread (β) and their Newey-West (1987) adjusted *t*-statistics from the multivariate rolling regressions for the sample period of January 4, 1996 to September 10, 2008. The volatility spread is measured by OWVS as defined in Table 1. X_t includes the lagged excess return on the S&P 500 index and the lagged macrovariables (DEF, TERM, RREL, DP) defined in Table 2. The dependent variable is the one-week ahead excess market returns. The rolling window is set to be half the entire sample period and rolled forward one period for each regression:

$$R_{t+1} = \alpha + \gamma \cdot VIXSQ_t + \beta \cdot OWVS_t + \theta \cdot X_t + \varepsilon_{t+1}$$



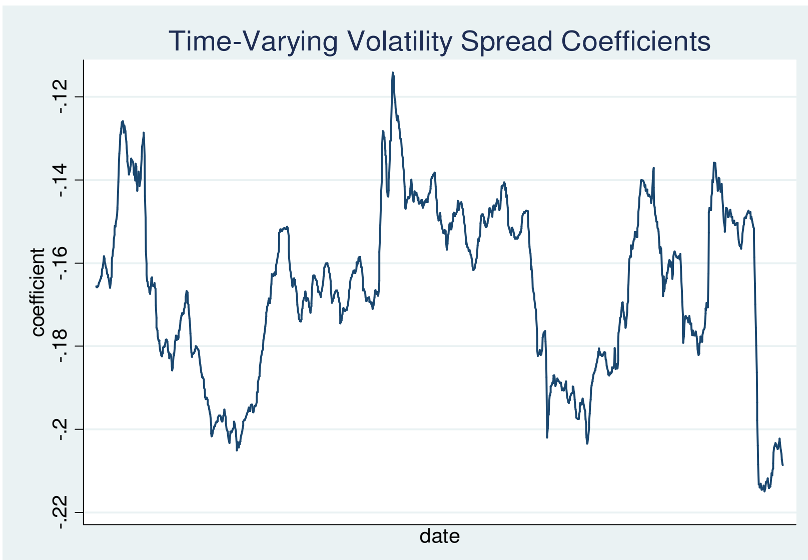


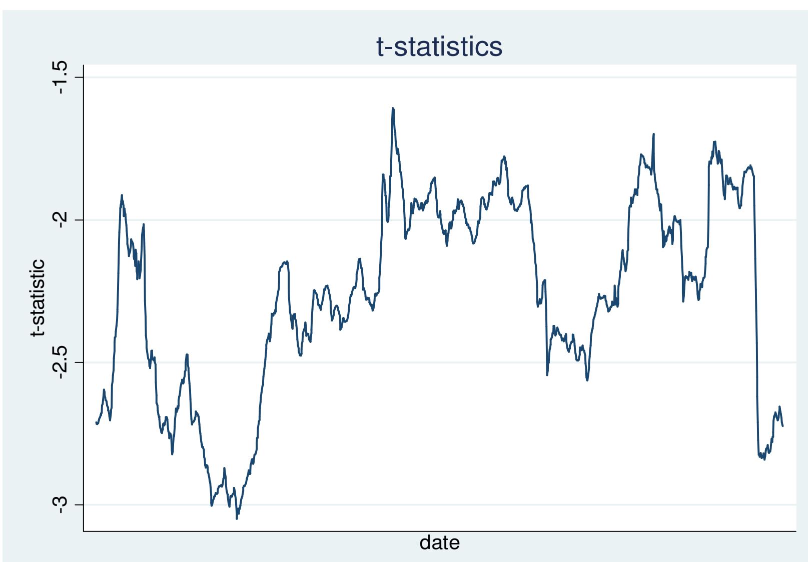
	Mean	Median	Std. Dev.	Min	Max
B	-0.11099	-0.11045	0.01688	-0.14299	-0.07580

Figure 3. Time-Varying Volatility Spread Coefficients (Biweekly)

These figures present the coefficients of volatility spread (β) and their Newey-West (1987) adjusted *t*-statistics from the multivariate rolling regressions for the sample period of January 4, 1996 to September 10, 2008. The volatility spread is measured by OWVS as defined in Table 1. X_t includes the lagged excess return on the S&P 500 index and the lagged macrovariables (DEF, TERM, RREL, DP) defined in Table 2. The dependent variable is the two-week ahead excess market returns. The rolling window is set to be half the entire sample period and rolled forward one period for each regression:

$$R_{t+1} = \alpha + \gamma \cdot VIXSQ_t + \beta \cdot OWVS_t + \theta \cdot X_t + \varepsilon_{t+1}$$



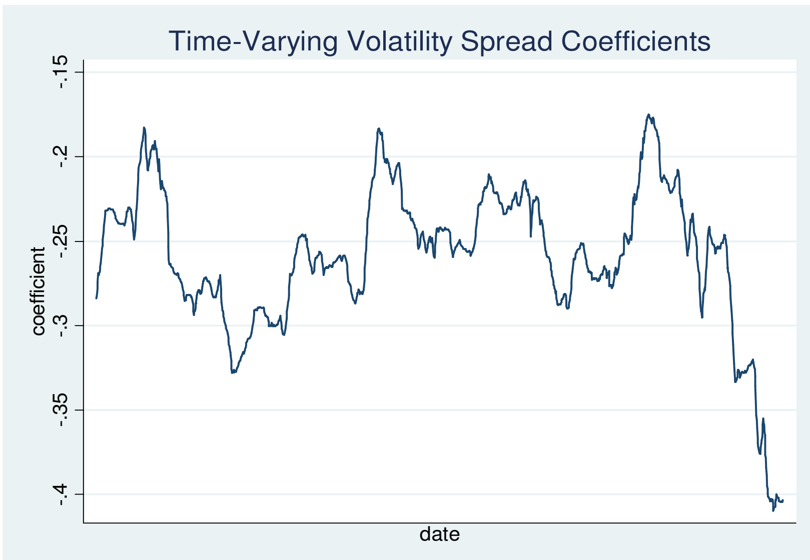


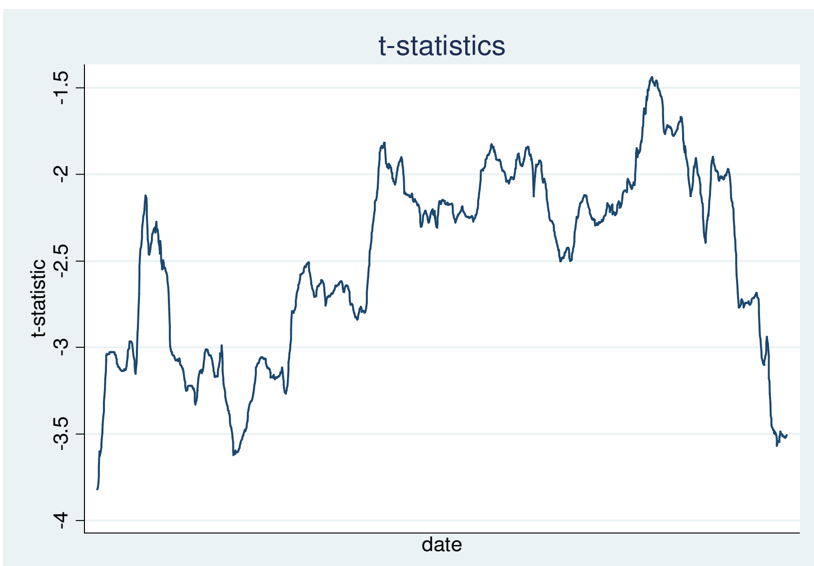
	Mean	Median	Std. Dev.	Min	Max
β	-0.16611	-0.16436	0.02085	-0.21492	-0.11407

Figure 4. Time-Varying Volatility Spread Coefficients (Monthly)

These figures present the coefficients of volatility spread (β) and their Newey-West (1987) adjusted *t*-statistics from the multivariate rolling regressions for the sample period of January 4, 1996 to September 10, 2008. The volatility spread is measured by OWVS as defined in Table 1. X_t includes the lagged excess return on the S&P 500 index and the lagged macrovariables (DEF, TERM, RREL, DP) defined in Table 2. The dependent variable is the one-month ahead excess market returns. The rolling window is set to be half the entire sample period and rolled forward one period for each regression:

$$R_{t+1} = \alpha + \gamma \cdot VIXSQ_t + \beta \cdot OWVS_t + \theta \cdot X_t + \varepsilon_{t+1}$$



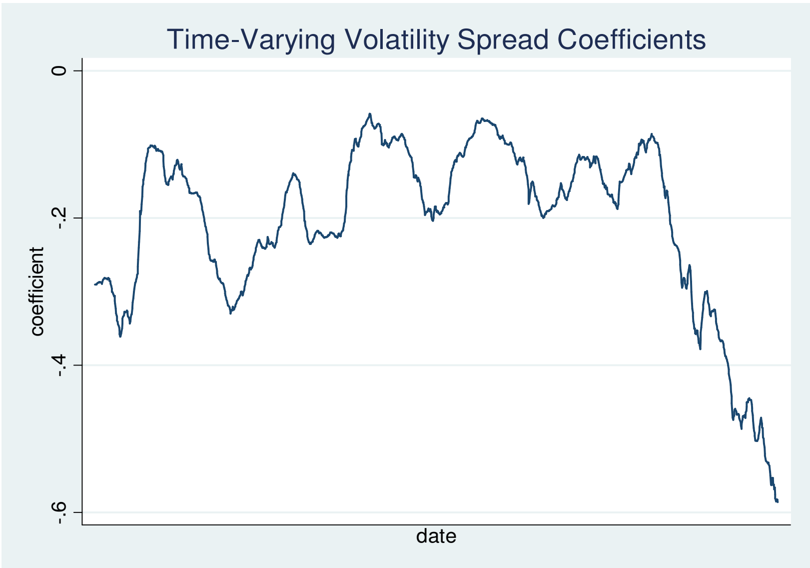


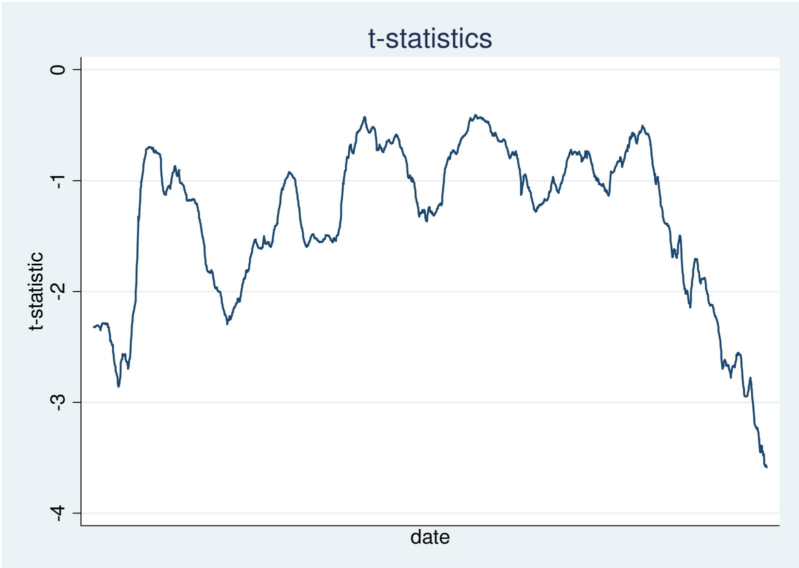
	Mean	Median	Std. Dev.	Min	Max
β	-0.25907	-0.25546	0.04267	-0.40949	-0.17481

Figure 5. Time-Varying Volatility Spread Coefficients (Trimonthly)

These figures present the coefficients of volatility spread (β) and their Newey-West (1987) adjusted *t*-statistics from the multivariate rolling regressions for the sample period of January 4, 1996 to September 10, 2008. The volatility spread is measured by OWVS as defined in Table 1. X_t includes the lagged excess return on the S&P 500 index and the lagged macrovariables (DEF, TERM, RREL, DP) defined in Table 2. The dependent variable is the three-month ahead excess market returns. The rolling window is set to be half the entire sample period and rolled forward one period for each regression:

$$R_{t+1} = \alpha + \gamma \cdot VIXSQ_t + \beta \cdot OWVS_t + \theta \cdot X_t + \varepsilon_{t+1}$$





	Mean	Median	Std. Dev.	Min	Max
β	-0.20535	-0.17385	0.11276	-0.58647	-0.05826

CHAPTER 3

Deviations From Put-Call Parity and Earnings Announcement Returns

1. Introduction

This study investigates whether information flow from option markets to stock markets influences the predictive ability of deviations from put-call parity on stock returns by conditioning on earnings announcements. I find that stocks with relatively expensive call (put) options before earnings announcements earn significantly positive (negative) abnormal returns during a two-day announcement window. Since stocks with relatively expensive call options earn significantly positive abnormal returns, this result cannot be solely explained by short sales restrictions. The degree of predictability is stronger under conditions when informed investors are more likely to trade in the option markets.

Put-call parity is a simple no arbitrage relationship which only hinges on the idea that the payoff of a stock can be synthetically replicated using call options, put options and bonds. Violations of put-call parity do not always represent arbitrage opportunities since factors such as dividend payments, transaction costs and the early exercise premium for American options can cause call and put option prices to deviate from put-call parity. Ofek and Richardson (2003) and Ofek, Richardson and Whitelaw (2004) find that violations of put-call parity may also occur when there are limits on arbitrage such as short sales restrictions. Another potential reason for these violations is the trading activity of informed investors. Bollen and Whaley (2004) and

Garleanu, Pedersen and Poteshman (2009) introduce demand-based option pricing models where the demand for an option affects its price. When the demand for a particular option contract is strong, competitive risk-averse option market makers cannot hedge their positions perfectly and they require a premium for taking this risk. In this type of equilibrium, one would expect a positive relationship between end-user demand and option expensiveness, which can be measured by implied volatility. If some investors have private information about future price increases (decreases), then they would demand more call (put) options which will increase the implied volatilities of call (put) options with respect to put (call) options. Therefore, the difference between put and call implied volatilities would increase (decrease) before stock price decreases (increases). Cremers and Weinbaum (2010) use these implied volatility differences to measure deviations from put-call parity and find that deviations from put-call parity can predict stock returns up to four weeks.

If the trading activity of informed traders is an important driver of deviations from put-call parity, then the predictability of stock returns should be more pronounced during major information events such as earnings announcements. Deviations of put-call parity are measured by the implied volatility difference between strike price and expiration date matched put and call options. One has to note that the existence of volatility spreads do not necessarily indicate arbitrage opportunities since options on individual stocks are American and strict put-call parity relationships take the form of an inequality due to early exercise premia. In the spirit of demand-based option pricing models, volatility spreads are just a means of capturing relative price pressures in the option market, hence it is more appropriate to use the term “deviation” rather than “violation”.

I find that when stocks are sorted based on their volatility spreads one day before earnings announcement dates, on average, a portfolio that includes stocks with the smallest volatility spreads (relatively more expensive call options) earns a five-factor adjusted abnormal return of 57.46 basis points (*t*-statistic = 4.15) whereas a portfolio that includes stocks with the largest volatility spreads (relatively more expensive put options) earns a five-factor adjusted abnormal return of -37.14 basis points (*t*-statistic = -2.53) during the earnings announcement window. The abnormal return difference between these two portfolios is 94.60 basis points. Together with the one-week hedge portfolio return of 20 basis points that Cremers and Weinbaum (2010) uncover, this finding is consistent with the idea that the predictability of stock returns by deviations from put-call parity should be stronger during periods that are informationally intensive. This result cannot be explained by short sales restrictions since the portfolio that buys stocks with relatively high call implied volatilities earns a significantly positive abnormal return. If the deviations from put-call parity could solely be explained by short sales restrictions, we would expect the predictability to be concentrated on stocks with relatively expensive puts. These results are robust if value-weighted rather than equal-weighted portfolio returns are used in the analysis. Measuring deviations from put-call parity using the average volatility spread over the pre-announcement week or scaling this average weekly volatility spread by the average volatility spread over the pre-announcement month do not alter the results.

I also look at the changes in the volatility spreads in the period preceding the earnings announcements rather than focusing only on volatility spread levels because deviations from put-call parity should change as the option market participants anticipate the magnitude and direction of the announcement returns. I double-sort stocks with respect to their volatility spread levels one day before the earnings announcements and the changes in their volatility spreads during the pre-announcement week. The abnormal return difference between a portfolio that buys stocks with both a low level and a large decrease of volatility spreads and a portfolio that buys stocks with a high level and a large increase of volatility spreads is about 2 percentage points during the earnings announcement window, on average. The portfolio that buys stocks with relatively expensive calls earns 114.10 basis points (*t*-statistic = 4.15) whereas the portfolio that buys stocks with relatively expensive puts earns -81.73 basis points (*t*-statistic = -2.47). I also find that the results are similar during both halves of the sample period which indicates that the degree of announcement return predictability has stayed strong over time.

I present three sets of results to argue that the return predictability during the earnings announcement period reflects informed trading. Easley, O'Hara and Srivinas (1998) find equilibrium conditions under which informed traders will be pooled with liquidity traders in the option market. Their model implies that when the option market is more liquid, the stock market is less liquid and the information environment is more asymmetric, informed traders will be more inclined to exploit their private information in the option market. First, I measure implied volatility spreads using only the most liquid options and find that the degree of announcement return predictability is stronger. Second, I show that announcement return predictability is stronger for stocks with higher PIN values, which measures the fraction of informed traders in the market. Third, stocks with higher illiquidity ratios exhibit stronger announcement return predictability.

Cross-sectional regressions reiterate the results from the portfolio analysis. After controlling for lagged stock returns and various contemporaneous and lagged risk factors such as excess market return, size, book-to-market, momentum and skewness, I find that there is a significantly negative relationship between the levels of and the changes in the volatility spreads before earnings announcements and the announcement returns. Regression analysis also confirm the finding that the significantly negative relationship between deviations from put-call parity and earnings announcement returns is stronger for stocks whose liquidity is low and probability of informed trading is high.

This study is related to the literature about the linkages between option and stock markets. The evidence had been mixed as far as the question whether option markets reveal information about future stock returns is concerned, however, many recent papers find that option trading behavior and option prices have predictive power for future stock returns. By documenting that deviations from put-call parity can predict stock returns around earnings announcements, the paper adds to this mounting evidence. Second, the study is related to the literature about deviations from put-call parity. I focus on a specific information event and find that stock return predictability is stronger under conditions when informed traders are more likely to use the option market. Additionally, I find that earnings announcement returns respond symmetrically to high and low levels and positive and negative changes of volatility spreads. These results collectively suggest that deviations from put-call parity cannot be solely explained by short sales restrictions and are related to the trading activity of informed traders. Third, the study is related to the literature about options behavior around earnings announcements. Previous research investigates how implied volatilities of individual options, option volumes, open interests and the slope of volatility smirks change before earnings announcements. This paper adds to these findings by focusing on deviations from put-call parity.

The paper is organized as follows. Section 2 is the literature review. I discuss deviations from put-call parity and option behavior around information events. Section 3 describes the methodology and data. Section 4 presents the main empirical results. Section 5 presents regression analysis for robustness check. Section 6 concludes.

2. Literature Review

2.1. Deviations from Put-Call Parity

Put-call parity is a no-arbitrage relation between the prices European style call and put options with the same strike prices and expiration dates. A portfolio which consists of a European call option and an amount of cash equal to the present value of the strike price and a portfolio which consists of a European put option and one share of the underlying stock have the same payoff at the expiration date. Therefore, these two portfolios should require the same investment. This relationship can be written as

$$S = PV(K) + C - P \tag{1}$$

where *S* is the stock price, *PV(K)* is the present value of the strike price. *C* and *P* are the prices of call and put options with the same strike prices and expiration dates, respectively.[17] For American options, equation (1) takes the form of an inequality since these options have a positive probability of early exercise. Therefore, put-call parity can be written as follows for American options:

$$S \geq PV(K) + C - P \ . \tag{2}$$

[17] For dividend paying stocks, one has to add the present value of the expected dividends until expiration date to the right-hand side of the relationship.

There is a strand of literature that investigates whether the above inequality holds. In a small sample of 15 stocks, Klemkosky and Resnick (1979) show that option markets are mostly efficient with respect to put-call parity. Brenner and Galai (1986) drive implied interest rates using put-call parity and document that implied interest rates track the market interest rates closely. Nispet (1992) identifies a significant number of violations of put-call parity in the London Traded Options Market, however, these violations do not prove to be exploitable when transaction costs such as commission costs are taken into account. One problem with these studies is that they omit the early exercise factor from the analysis. To abstract from the early exercise problem, Kamara and Miller (1995) only consider index options which are European. For these options, the violations of put-call parity are less frequent and smaller in magnitude compared to the earlier studies. Collectively, these studies suggest that violations of put-call parity do not represent arbitrage opportunities when dividend payments, transaction costs and early exercise value of American options are taken into account.

Recently, some studies offer limits on arbitrage such as short sales restrictions as a potential reason for violations of put-call parity. When put option prices are high enough compared to the corresponding call option and stock prices, the arbitrage strategy involves short selling the underlying stock. When there is a limit on short selling, violations of put-call parity can take place. Ofek and Richardson (2003) focus on Internet firms and present evidence for higher borrowing costs for short selling and greater violations of put-call parity for these stocks. They interpret these results as evidence supporting the effect of short sales restrictions on violations of put-call parity. Ofek, Richardson and Whitelaw (2004) look at a larger sample of firms and find that violations of put-call parity are asymmetric in the direction of short sales constraints. The magnitudes of these violations are significantly related to the cost and difficulty of short selling.

Violations of put-call parity can also occur because of informed trading by investors who possess private information. Demand-based option pricing models such as the ones in Bollen and Whaley (2004) and Garleanu, Pedersen and Poteshman (2009) introduce the idea that the demand for an option can affect its price. Informed traders might demand particular option contracts based on the content of their information and these demand pressures might cause their expensiveness (measured by implied volatility) of some option contracts to increase with respect to those of other option contracts. In other words, such demand pressures could cause call and put option prices to deviate from each other. I use the implied volatility spread between matched put and call options of an underlying security to measure such deviations. It should be emphasized that these volatility spreads measure “deviations” rather than “violations” from put-call parity because they do not represent arbitrage opportunities as the options written on individual stocks are American and their prices reflect early exercise premia. I find that the predictive ability of deviations from put-call parity for future earnings announcement returns is symmetric since both relatively expensive puts and relatively expensive calls contain information about announcement returns. Focusing on a significant information event augments the predictive power of deviations from put-call parity. The degree of predictability is stronger under conditions in which informed traders are more likely to use the option market. These findings collectively suggest that informed trading is an important driver of deviations from put-call parity.

2.2. Option Behavior Around Information Events

Different aspects of option trading behavior around various news events have been studied in the literature. Patell and Wolfson (1979) construct a simple model in which market participants expect the date of an information disclosure to be a period of temporarily increased stock price variability. Such behavior implies systematic changes in the volatility measures derived from option prices. The authors find that implied average standard deviations increase prior to earnings announcements and decline in the announcement period. This empirical regularity should not affect the analysis in this study because the increase in implied volatilities before earnings announcements apply equally to put and call options and the measure in this study is based on the implied volatility differences between these two option types. Donders and Vorst (1996) look at a larger sample of scheduled news announcements and Ederington and Lee (1993) focus on scheduled macroeconomic news on interest rate and foreign exchange futures. These studies confirm the finding that option implied volatilities reach a maximum on the eve of a news announcement and drop sharply and move back to their long-run levels after the news releases. Dubinsky and Johannes (2006) model this behavior by developing a pricing approach incorporating jumps on earning announcement dates. Their main predictions that implied volatilities should increase prior to earning announcements and decrease subsequent to the announcements are consistent with the previous empirical findings.[18]

More relevant to this study are a series of papers that are related to the information role of option markets before earnings announcements. Amin and Lee (1997) classify option trades as long trades if they involve buying a call or selling a put and as short trades if they involve selling a call or buying a put. They show that option traders initiate a greater proportion of long (short)

[18] See Whaley and Cheung (1982), Schachter (1988), Philbrick and Stephan (1993) and Donders, Kouwenberg and Vorst (1996) for other studies that investigate other aspects of options such as open interests, relative stock volumes and effective spreads before earnings announcements.

positions before earnings announcements for which reported earnings are greater (less) than the most recent analyst forecast. This finding supports the conjecture that option traders bring private information to the financial markets. My study concentrates on deviations from put-call parity rather than option volumes and investigates stock price reactions rather than merely classifying earnings announcement news as good or bad. Xing, Zhang and Zhao (2009) look at the differences between the implied volatilities between out-of-the-money put and at-the-money call options and find that these differences are higher before negative earnings surprises. The authors do not match put and call options based on strike prices and expiration dates, therefore their measure captures the slopes of the volatility smirks for individual options rather than deviations from put-call parity. Moreover, they do not investigate stock returns during earnings announcements. Finally, Diavatopoulos, Doran, Fodor and Peterson (2008) find that implied skewness and kurtosis changes extracted from option prices are strongly related to future stock returns around earning announcement dates. By investigating whether deviations from put-call parity can predict announcement returns, this study adds to the growing literature related to option behavior around news events.

3. Methodology and Data

3.1. Measuring Deviations from Put-Call Parity

Equation (1), the strict version of put-call parity for European options, should hold for any volatility parameter (σ) under the Black-Scholes (1973) formula. Therefore, the equation can be rearranged and restated as,

$$C(\sigma) + PV(K) = P(\sigma) + S \tag{3}$$

where $C(\sigma)$ and $P(\sigma)$ are call and put option prices implied by the Black-Scholes (1973) formula as a function of any volatility parameter σ. Combined with equation (1), equation (3) implies that, for every volatility parameter σ,

$$C(\sigma) - C = P(\sigma) - P \tag{4}$$

where C and P are the market prices of strike price and expiration date matched call and put options. The implied volatility of a put option is, by definition, the volatility parameter for which the Black-Scholes formula gives the market price of the put option. Therefore, one can write

$$P(IV\ put) = P\ . \tag{5}$$

It follows from equations (4) and (5) that,

$$C(IV\ put) = C\ . \tag{6}$$

Since the implied volatility of a call option is, by definition, the volatility parameter for which the Black-Scholes (1973) formula gives the market price of the call option, the following equation should also hold:

$$C(IV\ call) = C\ . \tag{7}$$

Now, equations (6) and (7) collectively imply that the Black-Scholes (1973) implied volatilities of put and call prices with the same strike prices and expiration dates should be equal for European options. In this study, I focus on options written on individual stocks, which are American. These options can be exercised before their expiration dates, thus their prices should reflect an early exercise premium. However, the Black-Scholes (1973) implied volatility difference between pairs of put and call options, adjusted for early exercise premia and dividends, can still be used to proxy for deviations from put-call parity.[19]

On a particular day, there might be multiple pairs of strike price and expiration date matched put and call options on a given stock. To construct a single measure of the volatility spread for each stock every day, I weight the implied volatility difference between matched put and call options by the average open interest of the call and put options in each pair.[20] I eliminate options for which open interest is non-positive and trading volume is missing.[21] One can formulate the weighted average volatility spread for stock *i* on day *t* as follows:

$$VS_{it} = \sum_{j=1}^{N_{it}} w_{jt}(IV\ put_{jt} - IV\ call_{jt}) \tag{8}$$

---

[19] See Figlewski and Webb (1993), Amin, Coval and Seyhun (2004), Ofek, Richardson and Whitelaw (2004) and Broadie, Chernov and Johannes (2007) for other studies that use volatility spreads to measure deviations from put-call parity. These studies implicitly assume the Black-Scholes formula in their treatments of the early exercise premia, therefore these premia are reflected in call and put option implied volatilities under lognormal distributions.

[20] The results continue to hold if the average volume of the call and put options in each pair is used as the weighting variable.

[21] Adding additional screens to the option data does not alter the results. Results are qualitatively the same after eliminating stocks whose price is less than $5, keeping only the options whose implied volatility is between 3% and 200% and whose time to expiration is within 10 to 60 days and deleting options whose price (average of best bid and best ask) is less than $0.125.

where j refers to pairs of put and call options with the same strike price and expiration date, N_{it} refers to the number of valid option pairs for stock i on day t, IV_{jt} is the implied volatility of the put or call option in option pair j and w_{jt} are the weights calculated based on the average open interest of the call option and put option in option pair j.

3.2. Data and Summary Statistics

The options data come from Ivy DB OptionMetrics. The database provides end-of-day bid and ask quotes, open interest, volume and implied volatility information on every call and put option on every individual stock traded on a U.S. exchange for the sample period from January 1996 to September 2008. I drop mutual or investment trust funds, American depositary receipts and exchange traded funds from the sample. At the beginning of the sample period, there are about 600,000 option observations per month. The number of monthly observations increases to about 4,000,000 at the end of the sample. OptionMetrics calculates implied volatilities using a binomial tree based on closing option prices and interest rates derived from LIBOR rates and settlement prices of Eurodollar futures after taking dividend payments and early exercise premia into account.[22] The data for share prices, daily stock returns and number of shares outstanding come from CRSP.[23] Earning announcement dates (day 0) and book value of equity data are from COMPUSTAT.[24]

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[22] Implied volatilities are not calculated when an option contract has non-standard settlement or a vega below 0.5. Moreover, if the midpoint of the option's bid/ask price is below intrinsic value or the underlying stock's price is not available, OptionMetrics does not report a value for implied volatility.

[23] I merge OptionMetrics and CRSP following Duarte, Lou and Sadka (2006). More specifically, I require the current CUSIP of a stock from OptionMetrics to be in the historical record of CUSIP's from CRSP. I delete observations for which the security identifier from CRSP (PERMNO) is assigned to more than one security identifier from OptionMetrics (SECID). I also delete stocks that appear in CRSP later than OptionMetrics and that have options appearing in OptionMetrics after their last day of appearance in CRSP.

[24] Financial firms and securities with CRSP share codes other than 10 or 11 are excluded from the sample.

Table 1 presents descriptive statistics on the implied volatility differences between strike price and expiration date matched put and call options, or volatility spreads. I measure these volatility spreads on the day preceding the earnings announcement. The descriptive statistics are provided for the full sample and two sub-periods (1996-2002 and 2003-2008). The final sample consists of 66,346 earnings announcement dates for 3,588 unique firms. There are 29,060 announcements in the first sub-period and 37,286 announcements in the second sub-period. Panel A shows that the average volatility spread for the full sample is 1.057% indicating that put options were more expensive than call options on average. Volatility spreads exhibit substantial variation. The average time-series standard deviation across firms is 5.993%. The overall, pooled standard deviation is 7.369% and the degree of variation is higher in the first sub-period. Volatility spreads are highly right-skewed and the degree of skewness is lower in the second sub-period.

Panel B presents the deciles of the distribution of volatility spreads. In the full sample, the 10^{th} percentile of the volatility spread is -3.610% and the 90^{th} percentile is 5.899%. This implies that volatility spreads are more pronounced in the direction of relatively more expensive puts. The sub-period summary statistics indicate that volatility spreads have become less pronounced in the later sub-period. The 10^{th} percentile of the volatility spread drops from -5.126% to -2.602% whereas the 90^{th} percentile of the volatility spread decreases from 6.899% to 5.006%.

Table 2 presents pre-formation characteristics and performances for quintile portfolios formed based on the level of volatility spreads. Letting the earnings announcement date to be day 0, the volatility spreads are measured on day -1. I group earnings announcements by the months in which they are made in order to construct these portfolios. I calculate averages of various characteristics for each quintile using this monthly system and then form grand averages over the full sample period. Doing so reduces the clustering of good or bad news in time. At the beginning of the sample period, there are 69 firms in each volatility spread quintile. This number increases to 170 firms at the end of the sample.

Panel A reports pre-formation characteristics for quintile portfolios. Stocks in quintile 1 (with relatively expensive calls) have a market capitalization of $3.3 billion and stocks in quintile 5 (with relatively expensive puts) have a market capitalization of $2.9 billion whereas stocks in quintile 3 have a market capitalization of $9.6 billion on average. Smaller stocks have lower liquidity and higher information asymmetry and the finding that stocks with larger deviations from put-call parity, on both sides, are smaller can be accounted for by these explanations.[25] These alternative interpretations are investigated later in the paper. I also find that stocks in the extreme quintiles are more volatile.[26] Market-to-book ratios monotonically increase as one goes from quintile 1 to 5. I also look at the skewness of the quintile portfolio returns since volatility spreads might be related to higher moments of the underlying risk-neutral return distributions. Although quintile 1 and quintile 5 have a higher skewness compared to the other quintiles, none of the skewness estimates are significantly different from zero (untabulated). Nevertheless, these summary statistics suggest the importance of controlling for various characteristics of quintile portfolios such as size, market-to-book and skewness.

[25] Although stocks in quintile 1 and 5 are smaller compared to the stocks in the other quintiles, these stocks cannot be characterized as small since the average NYSE size decile assignment for these stocks is 7. This is due to the fact that stocks with traded options tend to be larger.

[26] The standard deviation and skewness of quintile portfolio returns are calculated over the year preceding the portfolio formation.

Panel B reports the equal-weighted weekly pre-formation returns of the quintile portfolios.[27] Since the volatility spreads are measured on day -1, the one-week lagged return is measured from the closing of day -7 to the closing of day -2. The excess return for quintile 1 during the week preceding the portfolio formation is -65.67 basis points (*t*-statistic = -4.29) whereas the excess return for quintile 5 is 107.58 basis points for quintile 5 (*t*-statistic = 7.42). The weekly return difference between quintile 1 and 5 during the week before portfolio formation is -173.25 basis points and highly significant. I also look at the return difference between the extreme volatility spread quintiles during the second, third and fourth weeks before the quintile portfolios are formed. Although the excess portfolio returns increase almost monotonically from quintile 1 to quintile 5 during these weeks, the return differences between the extreme quintiles are not significant.

The finding that stocks with relatively expensive call options perform significantly worse than stocks with relatively expensive put options during the pre-announcement week is important. In other words, implied volatilities of put options increase more with respect to matched call options after stock price increases. This study argues that stocks with relatively expensive call options should have higher returns than stocks with relatively expensive put options during earnings announcement periods. Therefore, the volatility spread strategy that this study proposes is contrarian. I control for lagged weekly stock returns in the cross-sectional regressions in Section 5 so that the predictive ability of deviations from put-call parity for announcement returns is distinguished from short-term reversal patterns in stock prices.

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[27] The results in this study are qualitatively the same when value-weighted rather than equal-weighted returns are used in all the analyses.

4. Empirical Results

This section investigates the announcement window performances of portfolios formed based on levels and/or changes in volatility spreads preceding the announcement dates. I repeat the analysis in two sub-periods to see whether the findings are similar over time. I also investigate whether the predictive power of deviations from put-call parity is different when deviations are measured using more liquid options, when the underlying stock is less liquid or it has a more asymmetric information environment.

4.1. Post-formation Returns of Volatility Spread Quintiles

I sort stocks into quintiles based on their implied volatility spread signals preceding the earnings announcements. Letting the earnings announcement date to be day 0, I define the earnings announcement window to be days 0 and 1[28] and measure the announcement period returns as the returns on the underlying stocks during these two days. The levels of and changes in the volatility spreads are measured and quintile portfolios are formed on day -1. One empirical concern is that the non-synchronicity between option and stock markets might bias research results.[29] To alleviate this concern, I ignore overnight returns, measure the option signals based on the closing option prices on day -1 and start accruing the announcement returns from the opening of day 0.

Table 3 presents the post-formation returns of quintile portfolios formed in alternative ways. The first set of results is based on the levels of the volatility spreads. I form quintile

[28] The results are robust to alternative earnings announcement window specifications.

[29] The Chicago Board of Option Exchange closed at 4:10 PM EST until June 22nd, 1997 and at 4:02 PM EST after that date. In contrast, stock exchanges close at 4:00 PM EST. Battalio and Schultz (2006) look at intra-day options data to argue that the findings of Ofek, Richardson and Whitelaw (2004) are driven by non-synchronous prices inherent in the OptionMetrics database.

portfolios by sorting the volatility spreads of stocks on the closing of day -1 and report the returns on these portfolios from the opening of the earnings announcement day to the closing of the next day. I find that quintile 1 which contains stocks with relatively expensive call options earns an average return of 58.73 basis points during the earnings announcement window. In contrast, quintile 5 which contains stocks with relatively expensive put options earns an average return of -34.10 basis points. The difference between the returns of these two quintiles is 92.84 basis points with a highly significant *t*-statistic of 5.58. This result lends initial support to the hypothesis that deviations from put-call parity can predict announcement returns.

To rule out the possibility that this difference is driven by differences in firm characteristics documented in Table 2, I calculate abnormal returns using a five-factor model that includes market, size and book-to-market factors as in Fama and French (1993), a momentum factor as in Carhart (1997) and a total skewness factor.[30] I regress announcement returns on the contemporaneous values of these five factors and interpret the intercept, or alpha, as the abnormal return.[31] One can see that the abnormal returns to the quintile portfolios decrease monotonically from quintile 1 to quintile 5. The abnormal return for quintile 1 is 57.46 basis points (*t*-statistic = 4.15) whereas the abnormal return for quintile 5 is -37.14 basis points (*t*-statistic = -2.53). The difference between the abnormal returns is 94.60 basis points with a *t*-statistic of 5.40.

Cremers and Weinbaum (2010) conduct the same analysis by forming weekly quintiles based on volatility spread signals and investigate the one-week ahead returns of these portfolios.

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[30] I construct the skewness factor by ranking stocks based on the total skewness of their returns during the past year and forming three portfolios. The skewness factor is equal to the value-weighted return on the hedge portfolio which buys 30% of the stocks with the most negative skewness and sells 30% of the stocks with the most positive skewness.

[31] The data for the market, size, book-to-market and momentum factors come from Ken French's online data library.

However, they do not condition their analysis on earnings announcements which are informationally intensive periods for firms. They uncover a weekly abnormal return difference of 20 basis points between two extreme volatility spread portfolios. In contrast, I focus on earnings announcements and find that the abnormal return difference between extreme volatility spread portfolios is 94.57 basis points. This highlights the importance of focusing on significant information releases when investigating the predictive power deviations from put-call parity on announcement returns.

The results also show that the abnormal returns on the volatility spread quintiles is not limited to quintile 5 which contains stocks with relatively more expensive put options. If short-sale restrictions were the only driver of the predictability documented in this study, one would expect this predictability to be concentrated on only quintile 5. Short-sale restrictions may drive put option prices away from model values, however they should have no impact on call option prices. I find that stocks with relatively expensive call options earn significantly positive returns during earnings announcements. This evidence suggests that the findings in this study cannot be explained solely by short-sale restrictions.

Alternative measures for the levels of the volatility spreads are also considered. Rather than measuring the levels of the volatility spreads on day -1, I calculate the average volatility spreads over the week preceding the earnings announcements and form the quintile portfolios based on this alternative measure.[32] Moreover, I scale these average weekly volatility spreads by the average volatility spreads for each stock over the month preceding the announcements. In unreported results, I find that when volatility spread quintiles are formed based on the average volatility spreads during the pre-announcement week, the abnormal return difference between

[32] Stocks with at least two daily implied volatility spread observations during the pre-announcement week are considered.

extreme volatility spread quintiles is 55.12 basis points (*t*-statistic = 3.05). When these average weekly volatility spreads are scaled by the average monthly volatility spreads preceding the announcements and quintile portfolios are formed, the abnormal return difference becomes 60.38 basis points (*t*-statistic = 3.17). Finally, I calculate quintile portfolio returns by value-weighting rather than equal-weighting the individual stock returns and that the abnormal return difference between quintile 1 and quintile 5 is 73.47 basis points (*t*-statistic = 2.55).

The next set of results in Table 3 are based on quintile portfolios formed after sorting stocks according to the changes in their volatility spreads during the pre-announcement week. These changes are measured from the end of day -6 to the end of day -1 and the announcement returns start accruing from the opening of day 0. I find that quintile 1 which contains stocks whose volatility spreads decrease most during the pre-announcement week earns a five-factor adjusted abnormal return of 51.21 basis points with a *t*-statistic of 3.29. The abnormal return for quintile 5 is -21.20 with a *t*-statistic of -1.54. The abnormal return difference between the extreme volatility spread change quintiles is 72.40 with a *t*-statistic of 4.41. These results suggest that volatility spreads change due the anticipation of announcement returns during the pre-announcement week.

The final set of results in Table 3 considers both the levels of and the changes in volatility spreads. One would expect to find a larger abnormal return difference between stocks whose implied volatility spreads are lowest on day -1 and decrease most during the pre-announcement week and stocks whose implied volatility spreads are highest on day -1 and increase most during the pre-announcement week. The empirical results are consistent with this expectation. I construct 25 portfolios by sorting stocks into quintiles based on the level of their volatility spreads on day -1 and then sorting them into five additional groups based on the changes in their volatility spreads from day -6 to day -1. I report the post-formation performances of the diagonal portfolios that are constructed according to this double sorting procedure. Quintile (1,1) which includes stocks with relatively expensive call options earns a five-factor adjusted abnormal return of 114.10 basis points (*t*-statistic = 4.15). On the other hand, quintile (5,5) which includes stocks with relatively expensive put options earns an abnormal return of -81.73 basis points (*t*-statistic = -2.47). The abnormal return difference between the extreme quintiles is 195.83 basis points and highly significant. These results cannot be explained by short sale constraints as both extreme portfolios have abnormal returns significantly different from zero. Cremers and Weinbaum (2010) uncover an abnormal weekly return of 50 basis points for the same strategy, again highlighting the importance of focusing on information events.

4.2. Subsample Analysis

On one hand, it is possible that the degree of announcement return predictability has declined over time. Stock prices might adjust only gradually to the private information brought by informed investors, however, the public information embedded in option prices should be reflected in stock prices immediately. In the absence of serious market frictions, one would expect sophisticated investors to learn to exploit the predictability of announcement returns gradually. On the other hand, informed traders might have started using more synthetic short positions over time as suggested by Daske, Richardson and Tuna (2005) and hence the predictability of stock returns by deviations from put-call parity might get stronger in the later periods. In this section, I separate the full sample in two sub-periods and investigate whether the predictability of announcement returns persists through time.

Panel A of Table 4 concentrates on the sub-period from January 1996 to December 2002. When quintile portfolios are formed based on the levels of the volatility spreads on day -1, the abnormal return difference between the extreme quintiles is 84.88 basis points (*t*-statistic = 3.42). When I form the quintile portfolios based on the changes in the volatility spreads during the pre-announcement week, the abnormal return difference between the extreme quintiles is 68.95 basis points (*t*-statistic = 3.38). Finally, I double sort the stocks based on their volatility spread levels one day before the earnings announcements and the changes in their volatility spreads during the pre-announcement week. Stocks with relatively expensive call options (quintile (1,1)) earn an abnormal return which is 196.66 basis points (*t*-statistic = 3.56) more than that of stocks with relatively expensive put options (quintile (5,5)), on average. These results are very similar to those in the full sample. One also has to note that most of the predictability is driven by stocks with relatively expensive call options.

I conduct the same analysis for the second sub-period from January 2003 to September 2008. Panel B of Table 4 presents the results. When the quintile portfolios are constructed based on the volatility spread levels on day -1, stocks with relatively expensive call options earn 102.47 basis points (*t*-statistic = 4.07) more than stocks with relatively expensive put options. When the changes in volatility spreads during the pre-announcement week are used to construct the quintile portfolios, the abnormal return difference becomes 76.17 basis points (*t*-statistic = 2.81). Finally, double-sorting generates an abnormal return difference of 187.27 basis points (*t*-statistic = 3.19). Stocks with both a high level and large increase of volatility spreads earn an abnormal return of 902 basis points (*t*-statistic = 2.20) whereas stocks with a low level and large decrease of their volatility spreads earn an abnormal return of -97.25 points (*t*-statistic = -1.99). These results suggest that the degree of earnings announcement return predictability has stayed strong over time.

4.3. The Role of Option Liquidity

In their sequential trading model, Easley, O'Hara and Srivinas (1998) predict that informed investors will prefer to exploit their private information by trading options when the option markets are more liquid. Thus, if the deviations from put-call parity can predict earnings announcement returns, one would expect this predictability to be stronger when the deviations are measured using more liquid options. In this subsection, I sort all option pairs written on a particular stock on the day preceding the earnings announcement into three groups based on the average liquidity of the option pair. I calculate measures of deviation from put-call parity using both only the most liquid option pairs and only the least liquid option pairs. The aim of this analysis is to investigate whether there is any difference in announcement return predictability when deviations from put-call parity are measured using options of varying liquidity.

In Panel A of Table 5, the liquidity of each option pair is measured by the average bid-ask spread of its constituent call and put option. When the average bid-ask spread is low, the option pairs are deemed to be more liquid. For option pairs with low average bid-ask spreads, quintile 1 which includes stocks with high implied volatility spreads on day -1 earns an abnormal return of 61.32 basis points whereas quintile 5 which includes stocks with low implied volatility spreads on day -1 earns an abnormal return of -38.23 basis points. The abnormal returns to both of these extreme quintiles are highly significant. The abnormal return difference between the two quintiles is 99.56 basis points with a *t*-statistic of 7.31. In contrast, when deviations from put-call parity are measured using option pairs with high bid-ask spreads, the abnormal return difference between the two quintiles is 51.31 basis points with a *t*-statistic of 1.91. The difference between the extreme quintile abnormal return differences between the cases where deviations from put-call parity is measured using more liquid versus less liquid options is 48.24 basis points and highly significant. These findings suggest that deviations from put-call parity have stronger predictive power for announcement returns when more liquid option pairs are used to construct the deviations from put-call parity.

In Panel B of Table 5, the liquidity of each option pair is measured by the average volume of the call and the put in the pair. When option pairs with high average volumes are used to measure deviations from put-call parity, the abnormal return difference between extreme volatility spread quintiles is 105.93 basis points (*t*-statistic = 6.00). In contrast, this abnormal return difference shrinks to 45.89 basis points (*t*-statistic = 1.67) when only option pairs with low average volumes are used. The difference between extreme quintile abnormal return differences among the two cases is 60.05 basis points and highly significant with a *t*-statistic of 4.33. These empirical findings highlight the importance of option liquidity for the predictability of earnings announcement returns and supports the conjecture that informed traders are more inclined to use the option markets when they provide higher liquidity.

4.4. The Roles of Information Asymmetry and Stock Liquidity

When there is higher information asymmetry associated with a particular stock, it is more likely that informed traders will use the option markets according to Easley, O'Hara and Srivinas (1998). Therefore, one might expect the degree of earnings announcement predictability to be stronger when the probability of informed trading on a stock is higher. In this subsection, I test this conjecture and I also investigate whether deviations from put-call parity are more likely to be observed for stocks with higher PIN values.[33]

In Panel A of Table 6, I regress the absolute value of each volatility spread on day -1 for each firm-month on the PIN values and the logarithm of firm size. I also control for the liquidity of each stock since small stocks are expected to be less liquid and have less liquid options which may result in wider arbitrage bounds.[34] Average proportional bid-ask spreads in calls and puts are also included in the specification since these microstructural variables might also affect the magnitude of volatility spreads. The *t*-statistics presented in the table are based on robust standard errors clustered by firm. The results show that firms with higher PIN values tend to have larger volatility spreads in absolute magnitude. I also calculate relative volatility spreads for each firm-month as the absolute value of the difference between each volatility spread and the median volatility spread across all stocks during that particular month. When relative volatility spreads are regressed on PIN and the control variables, I find that the coefficient of PIN is still significantly positive.

Next, I attempt to answer the question whether the degree of earnings announcement return predictability is stronger for stocks with higher PIN values. To test this conjecture, I double sort stocks with respect to their PIN values and their volatility spread levels on the day before the announcement date and consider their returns during the announcement window. The results are presented on Panel B of Table 6. The abnormal return difference between extreme volatility spread quintiles is 16.64 basis points with a *t*-statistic of 0.81 for the lowest PIN

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[33] I would like to thank Stephen Brown from New York University for sharing his PIN dataset. I merge this dataset to my data using PERMNO's. PIN measures the fraction of informed traders in the market for a particular stock.

[34] In these regressions, I use the Amihud (2002) illiquidity ratio to proxy for the liquidity of each stock. The results are qualitatively similar when Amivest liquidity ratio (Amihud, Mendelson and Lauterbach (1997)) or Pastor and Stambaugh (2003) reversal measure are used. This data is obtained from Joel Hasbrouck's website at New York University.

quintile. However, these abnormal return differences increase monotonically moving to the higher PIN quintiles. For the quintile which contains stocks with the largest PIN values, the abnormal return difference between extreme volatility spread quintiles becomes 137.54 basis points with a *t*-statistic of 4.07. These results suggest that information asymmetry, proxied by the probability of informed trading, has an important role in the predictability of announcement returns by deviations from put-call parity.

Another prediction of the sequential trading model of Easley, O'Hara and Srivinas (1998) is that informed investors would be more inclined to trade options when the liquidity of the underlying equities is lower. The regression in Panel A of Table 6 includes the Amihud illiquidity ratio as an independent variable. After controlling for firm size, probability of informed trading and average bid-ask spreads in call and put options, I find that the illiquidity ratio and the absolute value of the volatility spreads are positively and significantly related. In Panel C, I test whether the predictive power of deviations from put-call parity for announcement returns is stronger when the liquidity of the underlying stocks is lower. I consider double sorts on illiquidity ratios and volatility spreads for this purpose. I find that for the quintile which includes the most liquid stocks, the abnormal return difference between the extreme volatility spread quintiles is 85.17 basis points with a *t*-statistic of 2.21. Although the abnormal returns do not change monotonically from the highest stock liquidity quintile to the lowest stock liquidity quintile, I find that the abnormal return difference between the extreme volatility spread quintiles for the stocks with the lowest liquidity is 184.19 basis points with a *t*-statistic of 3.94. These results support the hypothesis that informed traders prefer using the options market when the underlying stocks are less liquid.

5. Regression Analysis

In previous sections, I report evidence that deviations from put-call parity can predict earnings announcement returns and this predictability is stronger under conditions when informed investors are more likely to exploit their private information in the option markets. In this section, I retest these hypotheses in a panel regression setting after controlling for various risk factors and past stock returns.

5.1. Predictability of Earnings Announcement Returns

Table 7 presents the results for pooled panel regressions to investigate the ability of deviations from put-call parity to predict stock returns during earnings announcement periods. The dependent variable in all the regressions is the individual stock returns from the opening of the earnings announcement date to the closing of the next trading day. I control for various contemporaneous risk factors to make sure that the results are not driven by different risk characteristics for individual stocks. Specifically, I control for the market, size and book-to-market factors of Fama and French (1993), momentum factor of Carhart (1997) and a skewness factor. I also add the lagged weekly stock returns (from day -6 to day -1) and lagged risk factors to all the specifications to control for any autocorrelation and short-term reversal associated with stock returns. The *t*-statistics reported in the table are based on robust standard errors clustered by firm.

The first column in Table 7 includes the level of the volatility spread one day before the earnings announcement date in the regression specification. The coefficient of the level of the volatility spread is significantly negative. In the second regression, the change in the volatility spread during the pre-announcement week is used rather than the level of the volatility spread. I find a significantly negative relationship between changes in the volatility spreads and future announcement returns. In the third regression, both the level of and the change in the volatility spreads are included in the regressions. Both variables have significantly negative coefficients indicating that both volatility spread signals matter and their impacts on announcement returns are distinct. These results are consistent with the findings from the portfolio analyses.

The last three regressions replace the actual values of levels of and changes in volatility spreads by quintile dummies. I again sort stocks into quintile portfolios based on their volatility spread signals before the earnings announcements. I regress the announcement returns on the control variables and the quintile dummies. In the fourth column, I include the quintile dummies for the volatility spread levels in the specification. The coefficient associated with the lowest quintile dummy is significantly positive indicating an abnormal return of 30 basis points for these stocks. In contrast, the coefficient associated with the highest quintile dummy is significantly negative indicating an abnormal return of -40 basis points for these stocks. The abnormal return difference between these two extreme quintiles is 70 basis points. In the fifth column, the quintile dummies are based on the changes in the volatility spreads. The coefficient of the lowest quintile dummy is positive, albeit not significant. The coefficient for the highest change quintile dummy is significantly negative. The last column includes quintile dummies based on both volatility spread level and change quintiles. The results are similar to those in the fourth and fifth columns. Stocks with relatively expensive put (call) options and stocks that experience the largest increases (decreases) in their volatility spreads earn significantly negative (positive) abnormal returns.

In all the regression specifications, one-week stock returns preceding the earnings announcements have a significantly negative relationship with the announcement returns indicating the importance of short-term reversals in the sample. However, this does not alter the results from the portfolio analysis in the previous section. Deviations from put-call parity can still predict earning announcement returns.

5.2. The Role of Information Asymmetry and Stock Liquidity

In the portfolio analysis, it was documented that the predictability of announcement returns by volatility spreads is stronger for stocks that are less liquid and have a higher probability of informed trading. In this subsection, I test these hypotheses using panel regressions of announcement returns on volatility spread signals and interactions of these signals with PIN or illiquidity dummies. Each regression in Table 8 includes contemporaneous and lagged risk factors and lagged weekly stock returns as control variables. Two-day announcement returns start accruing from the opening of the earnings announcement date and *t*-statistics are based on robust standard errors clustered by firm.

The first two regressions in Table 8 investigate whether information asymmetry has an impact on the relationship between deviations from put-call parity and announcement returns. I create two dummy variables associated with PIN. “PIN low dummy” equals one for stocks that are in the lowest probability of informed trading quintile each month. Similarly, “PIN high dummy” equals one for stocks that are in the highest probability of informed trading quintile each month. I interact these dummies with the levels of volatility spreads in column 1 and the changes in volatility spreads in column 2. Then, I include these interaction terms in the regressions along with the control variables and the actual levels of and changes in volatility spreads. Similar to Table 8, both the level of and the change in volatility spreads have significantly negative coefficients. More importantly, the coefficient associated with PIN low dummy interaction is significantly positive whereas the coefficient associated with PIN high dummy interaction is significantly negative. The Wald statistic rejects the hypothesis that the coefficients of the two interaction terms are equal with a *p*-value of 0.010. These results suggest that there is more announcement return predictability when the underlying stocks have more information asymmetry.

I run the same regressions after replacing the PIN quintile dummy interactions with the Amihud illiquidity ratio quintile dummy interactions. The results are presented in the last two columns of Table 8. As before, both the level of and the change in volatility spreads have significantly negative coefficients. Amihud low dummy interactions have positive coefficients implying that the degree of predictability is less for stocks with higher liquidity. In contrast, the predictability of announcement returns is stronger for stocks with lower liquidity as suggested by the negative coefficients of Amihud high dummy interactions. Although the coefficients of the interaction variables are not significantly different from zero, with the exception of Amihud low dummy interaction in the change of volatility spread regression, I find that the Wald statistic rejects the equality of the low and high illiquidity dummy interaction coefficients with a *p*-value of 0.0490. These results highlight the importance of stock liquidity for the predictability of earnings announcement returns.

6. Conclusion

Cremers and Weinbaum (2010) find that deviations from put-call parity can predict stock returns. This study conjectures that if deviations from put-call parity are driven by the trading activities of informed traders, then the documented predictability should be stronger around significant information releases. For this purpose, I focus on earnings announcements and find that deviations from put-call parity can predict announcement returns. I use volatility spreads defined as the weighted average differences of implied volatilities between strike price and expiration date matched put and call options to measure these deviations and find that stocks with relatively expensive call options earn significantly higher returns compared to stocks with relatively expensive put options during a two-day announcement window. The abnormal return difference between stocks with both a low level and large decrease of volatility spreads and stocks with both a high level and large increase of volatility spreads is about 2 percent during a two-day earnings announcement window.

I argue that the predictability of announcement returns by deviations from put-call parity is due to the existence of informed traders in the option markets. First, coupled with the findings of Cremers and Weinbaum (2010), the strong predictability of earnings announcement returns shows the importance of conditioning on information events. Second, I find that stocks with relatively expensive call options earn significantly positive abnormal returns during the announcement window which rules out short sales restrictions as the sole explanation of the results. Finally, the degree of announcement return predictability is shown to be stronger when informed investors are more likely to trade in the option markets. Specifically, I find that the degree of predictability is higher when deviations from put-call parity are measured using more liquid options, liquidity of the underlying equities is lower and the information environment is more asymmetric.

Table 1. Descriptive Statistics for Volatility Spreads

This table presents various descriptive statistics for volatility spreads. Volatility spreads are defined as the open interest weighted average implied volatility differences between strike price and expiration date matched puts and calls across option pairs for an underlying stock on the day preceding the earnings announcements. The full sample period is January 1996 to September 2008. Results are also reported for two sub-periods: January 1996 to December 2002 and January 2003 to September 2008. Panel A reports the mean volatility spread (cross-sectional average of time-series means across firms), the average time series standard deviation across firms and the overall pooled standard deviation and skewness. Panel B reports decile breakpoints. All the descriptive statistics are reported in percentages.

	Full Sample	1996-2002	2003-2008
Panel A: Summary Statistics			
Mean	1.057	0.955	1.137
Standard deviation (time-series)	5.993	6.614	4.723
Standard deviation (pooled)	7.369	8.327	6.524
Skewness	4.671	5.776	2.642
Number of observations	66,346	29,060	37,286
Panel B: Percentiles			
10^{th}	-3.610	-5.126	-2.602
20^{th}	-1.510	-2.249	-1.100
30^{th}	-0.502	-0.857	-0.318
40^{th}	0.192	0.081	0.251
50^{th}	0.784	0.845	0.751
60^{th}	1.416	1.679	1.277
70^{th}	2.210	2.692	1.924
80^{th}	3.410	4.176	2.882
90^{th}	5.899	6.899	5.006

Table 2. Pre-formation Characteristics and Performances

This table presents pre-formation characteristics and performances for quintile portfolios formed based on volatility spreads as defined in Table 1. Every month, stocks are sorted into quintiles based on their volatility spreads one day before their earnings announcement dates. Panel A shows the pre-formation average market value of equity (in $ millions), market-to-book ratio, standard deviation and skewness (both estimated over the pre-announcement year) for each quintile portfolio. Panel B presents the pre-formation equal-weighted quintile portfolio returns over the first, second, third and fourth weeks preceding the earnings announcement. I report average returns, average returns in excess of the NYSE/AMEX/NASDAQ index, in basis points and t-statistics associated with the excess returns. The last two columns represent the average and excess return differences between the extreme volatility spread quintiles and *t*-statistics associated with these differences, respectively.

		Volatility Spread Quintiles						
		1	**2**	**3**	**4**	**5**	**(1-5)**	**t-stat**
Panel A: Pre-formation characteristics								
Market value of equity		3,285	7,773	9,634	7,571	2,945		
Market-to-book ratio		2.17	2.39	2.52	2.44	3.74		
Standard Deviation		0.034	0.028	0.027	0.029	0.034		
Skewness		0.192	0.177	0.137	0.178	0.224		
Panel B: Pre-formation performance								
First week	mean return	-61.79	102.74	76.22	118.15	134.83	-196.62	[-6.26]
	excess return	-65.67	4.73	61.12	95.5	107.58	-173.25	[-8.22]
	t-stat	[-4.29]	[0.45]	[5.99]	[9.68]	[7.42]		
Second week	mean return	13.84	24.98	23.58	50.13	38.46	-24.62	[-0.84]
	excess return	-4.07	6.78	5.46	32.67	26.63	-30.70	[-1.50]
	t-stat	[-0.28]	[0.72]	[0.58]	[2.78]	[1.86]		
Third week	mean return	-4.36	26.92	40.43	44.74	23.61	-27.97	[-0.94]
	excess return	-25.73	4.09	18.19	24.64	3.83	-29.56	[-1.45]
	t-stat	[-1.66]	[0.41]	[1.71]	[2.50]	[0.29]		
Fourth week	mean return	3.11	7.89	16.43	37.86	38.29	-35.18	[-1.19]
	excess return	-18.37	-10.85	1.46	17.62	19.47	-37.84	[-1.82]
	t-stat	[-1.21]	[-1.27]	[0.16]	[1.62]	[1.37]		

Table 3. Returns on Portfolios Formed Based on Volatility Spread Signals

This table presents earnings announcement returns on quintile portfolios formed based on various pre-announcement volatility spread signals. The announcement returns accrue from the opening of the earnings announcement day to the closing of the next day. I report equal-weighted quintile portfolio returns, alphas and *t*-statistics associated with alphas for each volatility spread quintile. Alphas are with respect to the market, size, book-to-market (Fama and French (1993)), momentum (Carhart (1997)) and skewness factors. In "Level" results, quintile portfolios are formed based on the level of the volatility spreads one day before the earnings announcement dates. In "Change" results, quintile portfolios are formed based on the change in volatility spreads during the pre-announcement week. "Level/Change" results are associated with double-sorts based on both volatility spread levels and volatility spread changes. The last two columns represent the average return and alpha differences between the extreme volatility spread quintiles and *t*-statistics associated with these differences.

		VOLATILITY SPREAD QUINTILES					**(1-5)**	
		1	**2**	**3**	**4**	**5**	**return**	**alpha**
Level	mean ret	58.73	43.59	10.94	15.30	-34.10	92.84	94.60
	alpha	57.46	43.44	15.47	10.12	-37.14	[5.58]	[5.40]
	t-stat	[4.15]	[3.14]	[1.26]	[0.83]	[-2.53]		
		1	**2**	**3**	**4**	**5**		
Change	mean ret	53.65	35.11	35.99	-5.80	-22.54	76.19	72.40
	alpha	51.21	30.45	34.71	-3.97	-21.20	[4.77]	[4.41]
	t-stat	[3.29]	[2.32]	[2.70]	[-0.36]	[-1.54]		
		1,1	**2,2**	**3,3**	**4,4**	**5,5**		
Change/ Level	mean ret	97.47	12.67	50.29	-12.97	-85.13	182.61	195.83
	alpha	114.10	15.35	39.42	-23.62	-81.73	[4.93]	[4.92]
	t-stat	[4.15]	[0.63]	[1.77]	[-0.85]	[-2.47]		

Table 4. Subsample Analysis

This table presents earnings announcement returns on quintile portfolios formed based on various pre-announcement volatility spread signals. Results are presented for two sub-periods. Panel A reports results for the sub-period from January 1996 to December 2002. Panel B reports results for the sub-period from January 2003 to September 2008. The announcement returns accrue from the opening of the earnings announcement day to the closing of the next day. I report equal-weighted quintile portfolio returns, alphas and *t*-statistics associated with alphas for each volatility spread quintile. Alphas are with respect to the market, size, book-to-market (Fama and French (1993)), momentum (Carhart (1997)) and skewness factors. In "Level" results, quintile portfolios are formed based on the level of the volatility spreads one day before the earnings announcement dates. In "Change" results, quintile portfolios are formed based on the change in volatility spreads during the pre-announcement week. "Level/Change" results are associated with double-sorts based on both volatility spread levels and volatility spread changes. The last two columns represent the average return and alpha differences between the extreme volatility spread quintiles and *t*-statistics associated with these differences.

Panel A (1996-2002)

		VOLATILITY SPREAD QUINTILES					(1-5)	
		1	**2**	**3**	**4**	**5**	**return**	**alpha**
Level	mean ret	77.07	36.60	6.50	29.20	-9.40	86.49	84.88
	alpha	86.26	45.00	12.83	26.55	1.37	[3.67]	[3.42]
	t-stat	[4.87]	[2.23]	[0.67]	[1.33]	[0.06]		
		1	**2**	**3**	**4**	**5**		
Change	mean ret	68.05	48.33	30.62	1.77	-11.63	79.68	68.95
	alpha	71.46	47.43	38.13	15.11	2.52	[3.87]	[3.38]
	t-stat	[3.40]	[2.49]	[2.00]	[0.97]	[0.12]		
		1,1	**2,2**	**3,3**	**4,4**	**5,5**		
Change/ Level	mean ret	109.10	0.82	51.60	9.77	-82.43	191.53	196.66
	alpha	132.80	7.98	42.18	6.32	-63.87	[3.78]	[3.56]
	t-stat	[3.48]	[0.21]	[1.20]	[0.15]	[-1.38]		

Panel B (2003-2008)

		VOLATILITY SPREAD QUINTILES					(1-5)	
		1	**2**	**3**	**4**	**5**	**return**	**alpha**
Level	mean ret	36.40	52.10	23.45	-1.63	-64.16	100.56	102.47
	alpha	21.56	43.45	18.95	-9.30	-80.91	[4.31]	[4.07]
	t-stat	[1.02]	[2.30]	[1.29]	[-0.73]	[-4.36]		
		1	**2**	**3**	**4**	**5**		
Change	mean ret	36.12	19.02	42.54	-15.17	-35.83	71.94	76.17
	alpha	26.54	13.11	29.24	-24.76	-49.63	[2.86]	[2.81]
	t-stat	[1.13]	[0.73]	[1.72]	[-1.65]	[-2.86]		
		1,1	**2,2**	**3,3**	**4,4**	**5,5**		
Change/ Level	mean ret	83.32	27.11	48.69	-40.66	-88.42	171.74	187.27
	alpha	90.02	24.33	30.42	-53.03	-97.25	[3.14]	[3.19]
	t-stat	[2.20]	[0.88]	[1.27]	[-1.41]	[-1.99]		

Table 5. The Role of Option Liquidity

This table presents earnings announcement returns on quintile portfolios formed based on pre-announcement day volatility spread levels calculated using options with different liquidity characteristics. For every stock, all option pairs are sorted into three groups based on the average liquidity of the pair on the pre-announcement day and separate volatility spreads are calculated using option pairs of low and high liquidity. Liquidity of an option pair is measured using either its average bid/ask spread (Panel A) or its average volume (Panel B). The announcement returns accrue from the opening of the earnings announcement day to the closing of the next day. I report equal-weighted quintile portfolio returns, alphas and *t*-statistics associated with alphas for each volatility spread quintile. Alphas are with respect to the market, size, book-to-market (Fama and French (1993)), momentum (Carhart (1997)) and skewness factors. The last two columns represent the average return and alpha differences between the extreme volatility spread quintiles and *t*-statistics associated with these differences.

		VOLATILITY SPREAD QUINTILES					**(1-5)**	
Panel A: Bid/Ask Spread								
		1	**2**	**3**	**4**	**5**	**return**	**alpha**
More Liquid	mean ret	66.37	48.13	8.65	17.38	-39.27	105.64	99.56
	alpha	61.32	49.08	12.13	20.07	-38.23	[7.23]	[7.31]
	t-stat	[5.02]	[2.97]	[1.33]	[0.91]	[-2.87]		
		1	**2**	**3**	**4**	**5**	**return**	**alpha**
Less Liquid	mean ret	39.12	29.23	14.66	17.82	-21.22	60.34	51.31
	alpha	33.54	30.02	12.55	19.01	-17.77	[2.43]	[1.91]
	t-stat	[2.88]	[2.97]	[0.67]	[0.87]	[-1.19]		
Panel B: Volume								
		1	**2**	**3**	**4**	**5**	**return**	**alpha**
More Liquid	mean ret	80.24	43.59	10.94	15.30	-23.25	103.49	105.93
	alpha	78.05	37.03	12.21	10.97	-27.88	[6.27]	[6.00]
	t-stat	[4.81]	[2.33]	[1.09]	[0.78]	[1.64]		
		1	**2**	**3**	**4**	**5**	**return**	**alpha**
Less Liquid	mean ret	23.12	24.16	15.21	3.26	-24.98	48.10	45.89
	alpha	26.13	43.44	15.47	-1.65	-19.76	[1.52]	[1.67]
	t-stat	[1.67]	[1.49]	[1.26]	[-0.18]	[-0.99]		

Table 6. The Roles of Information Asymmetry and Stock Liquidity

Panel A presents the regressions of absolute values of individual volatility spreads and relative volatility spreads on PIN, Amihud (2002) illiquidity ratio, size defined as the log of market value of equity and the average proportional bid-ask spreads in calls and puts. Relative volatility spread is equal to the difference between each volatility spread and the median volatility spread across all stocks during a particular month. The *t*-statistics reported in the panel are based on robust standard errors clustered by firm. Panel B (Panel C) presents earnings announcement returns on hedge portfolios formed based on double-sorts using PIN (Amihud illiquidity ratio) and volatility spread levels on the pre-announcement day. The announcement returns accrue from the opening of the earnings announcement day to the closing of the next day. I report alphas and *t*-statistics associated with these alphas for the hedge portfolios. Alphas are with respect to the market, size, book-to-market (Fama and French (1993)), momentum (Carhart (1997)) and skewness factors.

Panel A

	Volatility spread	Volatility spread	Rel. vol. spread	Rel. vol. spread
Intercept	0.1207	0.0952	0.1178	0.0962
	[34.67]	[29.13]	[32.90]	[29.43]
PIN		0.0138		0.0131
		[2.17]		[2.08]
Illiquidity ratio		0.0599		0.0609
		[3.98]		[4.07]
Size	-0.0101	-0.0084	-0.0102	-0.0087
	[-26.13]	[-23.24]	[-25.63]	[-23.81]
Call spread	0.0732	0.0658	0.0714	0.0652
	[13.21]	[11.95]	[12.89]	[11.44]
Put spread	0.0237	0.0192	0.0231	0.0187
	[5.27]	[4.51]	[5.09]	[4.60]

Panel B

		(1-5)
PIN (low)	alpha	16.64
	t-stat	[0.81]
PIN (2)	alpha	13.18
	t-stat	[0.38]
PIN (3)	alpha	36.75
	t-stat	[1.65]
PIN (4)	alpha	113.15
	t-stat	[2.34]
PIN (high)	alpha	137.54
	t-stat	[4.07]

Panel C

		(1-5)
Amihud(low)	alpha	85.17
	t-stat	[2.21]
Amihud (2)	alpha	94.19
	t-stat	[2.58]
Amihud (3)	alpha	26.52
	t-stat	[0.63]
Amihud (4)	alpha	60.64
	t-stat	[1.22]
Amihud (high)	alpha	184.19
	t-stat	[3.94]

Table 7. Panel Regressions

This table presents results for panel regressions of earnings announcement returns on various volatility spread signals or quintile dummies formed based on these signals. In the first three columns, volatility spread levels on the pre-announcement day and/or volatility spread changes during the pre-announcement week are included in the specification. In the last three columns, quintile dummies formed based on these volatility spread levels and/or changes replace the actual values of volatility spread signals. The announcement returns accrue from the opening of the earnings announcement day to the closing of the next day. All specifications include contemporaneous and lagged values of market, size, book-to-market (Fama and French (1993)), momentum (Carhart (1997)) and skewness factors. The stock returns during the pre-announcement week are also controlled for in each specification. The *t*-statistics are based on robust standard errors clustered by firm.

	1	**2**	**3**	**4**	**5**	**6**
Intercept	0.0023	0.0019	0.0023	0.0017	0.0023	0.0019
	[5.96]	[5.26]	[5.99]	[2.59]	[3.47]	[2.28]
Level of volatility spread	-0.0309		-0.0265			
	[-5.05]		[-4.17]			
Change of volatility spread		-0.0189	-0.0125			
		[-3.33]	[-2.13]			
dummy Q1 - level				0.0030		0.0029
				[2.88]		[2.60]
dummy Q2 - level				0.0021		0.0020
				[2.21]		[2.01]
dummy Q4 - level				-0.0003		0.0001
				[-0.28]		[0.00]
dummy Q5 - level				-0.0040		-0.0034
				[-3.77]		[-2.89]
dummy Q1 - change					0.0014	0.0013
					[1.29]	[1.02]
dummy Q2 - change					0.0011	0.0004
					[1.12]	[0.42]
dummy Q4 - change					-0.0008	-0.0002
					[-0.90]	[-0.22]
dummy Q5 - change					-0.0034	-0.0024
					[-3.20]	[-2.17]
Return [-6,-1]	-0.0690	-0.0694	-0.0694	-0.0683	-0.0689	-0.0682
	[-9.77]	[-9.80]	[-4.17]	[-9.57]	[-9.60]	[-9.52]
Five factors	Yes	Yes	Yes	Yes	Yes	Yes
Lagged five factors	Yes	Yes	Yes	Yes	Yes	Yes
R squared	3.17%	3.13%	3.17%	3.17%	3.14%	3.18%

Table 8. Panel Regressions: Information Asymmetry and Stock Liquidity

This table presents results for pooled, cross-sectional panel regressions of earnings announcement returns on various volatility spread signals or their interactions with quintile dummies formed based on either PIN (probability of informed trading) or Amihud (2002) illiquidity ratio. I sort stocks based on their PIN values or illiquidity ratios into quintiles each month. PIN low dummy (PIN high dummy) equals one for stocks with the lowest (highest) PIN values. Amihud low dummy (Amihud high dummy) equals one for stocks with the lowest (highest) illiquidity ratios. First and third columns include volatility spread levels on the pre-announcement day and second and fourth columns include volatility spread changes during the pre-announcement week in the specification. In the first two columns, these volatility spread signals are interacted with PIN low dummy and PIN high dummy. In the last two columns, the volatility spread signals are interacted with Amihud low dummy and Amihud high dummy. The announcement returns accrue from the opening of the earnings announcement day to the closing of the next day. All specifications include contemporaneous and lagged values of market, size, book-to-market (Fama and French (1993)), momentum (Carhart (1997)) and skewness factors. The stock returns during the pre-announcement week are also controlled for in each specification. The *t*-statistics are based on robust standard errors clustered by firm.

	1	**2**	**3**	**4**
Intercept	0.0023	0.0019	0.0023	0.0019
	[6.06]	[5.26]	[5.98]	[5.25]
Level of volatility spread	-0.0346		-0.0336	
	[-4.27]		[-4.06]	
Change of volatility spread		-0.0156		-0.0229
		[-2.07]		[-2.89]
PIN low dummy interaction	0.0198	0.0160		
	[2.75]	[2.60]		
PIN high dummy interaction	-0.0152	-0.0076		
	[-2.28]	[-1.97]		
Amihud low dummy interaction			0.0034	0.0203
			[0.75]	[2.83]
Amihud high dummy interaction			-0.0098	-0.0082
			[-1.88]	[-1.33]
Return [-6,-1]	-0.0688	-0.0694	-0.0689	-0.0693
	[-9.75]	[-9.81]	[-9.77]	[-9.81]
Five factors	Yes	Yes	Yes	Yes
Lagged five factors	Yes	Yes	Yes	Yes
R squared	3.17%	3.13%	3.17%	3.13%
Wald statistic p-value	0.0095	0.0103	0.0490	0.0271

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