ESSAYS ON OPTION MARKET INFORMATION CONTENT, MARKET SEGMENTATION AND FEAR

by

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ABSTRACT

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This dissertation consists of three essays. The first essay tests whether stock returns can be predicted using divergence from put-call parity. Using a robust methodology that controls for the early exercise premium of American put and call options, the study shows that stocks with upside divergence from put-call parity outperform stocks with downside divergence from put-call parity. Predictability is persistent over multiple holding periods and divergence is also predictive of tail events.

The second essay examines segmentation of equity and option markets in the presence of information asymmetry. The study uses the slope of the implied volatility skew as a proxy for negative jump risk, option implied stock price as a measure of deviation from put-call parity, and the daily short-sell volume ratio as a measure of negative information flow in the equity market. The option market based signals predict future returns more reliably than the short-sell based signals. Short-sellers only profit when their convictions line-up with negative signals in the option market.

The third essay introduces a measure of fear derived from the implied volatility smile. The study examines the relationship between fear and the cross section of option returns. The results show that put options written on stocks with high fear premium outperform put options written on stocks with low fear premium. Fear does not predict the realization of a tail event. This finding confirms the irrational nature of fear.

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CHAPTER 1

INTRODUCTION

Option market allows investors to hedge risk, speculate, or take advantage of insider information. Options have several properties that appeal to investors. The limited downside on long option positions make options ideal instruments for hedging. The high degree of leverage achievable combined with limited downside make the option market an attractive venue for investors with insider information (Xing et. al 2010, Chakravarty et. al. 2004). On the other hand, option trading can be motivated by miss-estimation of the risk involved with the underlying security (Stein 1989, Goyal and Sarreto 2009). Often such over-reaction is motivated by the fear of large adverse price jumps (Pan 2002). The dynamics of option prices are driven by all of the above mentioned factors. This study consists of three essays that aim to disentangle the complex relationships between options, underlying securities and expectations of stock and option market participants; both informed and un-informed.

The pricing of the options depend on investor's expectations about the future direction of the underlying security. As option prices move with the market forces, so do the implied volatilities of options. Implied volatility smiles, reflect the expectations about direction of the underlying security. At the same time, when option prices deviate from the well-known no-arbitrage condition of put-call-parity, it also reveals information about market expectations. Prior research shows, that deviations from put-call parity can predict future stock returns (Cremers and Weinbaum, 2010).

The complexity of the relationship between options, their underlying security, the informed and uninformed participants in the option and equity markets creates some very interesting questions. The fundamental question is what is the relationship between stocks and options that cannot be systematically determined by the application of an option pricing formula?

To address this question I investigate several pieces of the option pricing puzzle. The very first piece of the puzzle is to understand the nature of deviation from a systematic relationship. One such systematic relationship is put-call parity. The violation of this condition indicates the existence of different information sets in the options and stock markets. If such violations exist, the next logical inquiry is to find which information set is richer. If option traders are guided by a richer information set, the option market should lead the equity market. The first essay addresses the lead-lag relationship between the equity market and the option market. Using divergence from put-call parity, I show that it is possible to predict the direction of the underlying stock. My findings indicate that the option market leads the equity market.

Once the richer information set is identified, the next critical question is: what is the source of the discrepancy in the information content? Two hypotheses discussed in the literature are known as the informed trader hypothesis and the over-reaction hypothesis. In the first essay, I find results supporting the informed trader hypothesis. I find that divergence from put-call parity is predictive of the future direction of the underlying security. Furthermore, divergence is also predictive of large negative moves.

The second essay explores the source of the discrepancy in more detail. To pinpoint the fundamental difference between participants in the equity market and the option market, I ask whether equity market participants are less rational than option market participants. I construct long and short signals based on option and equity market prices. I find that the option market based signals are of higher quality than equity market based signals. Most importantly, short-sellers only profit when their convictions line-up with negative signals in the option market. In other words, when there are conflicting signals from equity and option markets, the option market signals predict the correct direction.

After confirming the fact that the option market information set is indeed superior, the question remains whether option traders are truly rational. In the third essay, I find that option traders are subject to miss-estimation as well. Option traders are prone to over-estimation of risk.

Using option market prices, I construct a new index that quantifies fear of a market crash. Put options written on stocks with high fear premium outperform put options written on stocks with low fear premium. Furthermore, fear does not predict the realization of a tail event. This finding confirms the irrational nature of fear.

CHAPTER 2

DIVERGENCE FROM PUT-CALL PARITY, TAIL RISK AND FUTURE STOCK RETURNS

2.1. Introduction

The put-call parity relationship is a well-known no arbitrage condition. In the presence of deviation from put-call parity, arbitrageurs can execute trades to make profits. In some cases, limits to arbitrage prevent efficient arbitrage. Although, not every violation is arbitrage-able, the information content of the degree of violation is valuable for predicting the risk of securities.

Prior studies find that put-call parity does not hold in the presence of short-sale constraints. However, short-sale constraints alone cannot account for the degree of mispricing between the two markets (Ofek et. al 2004, Lamont and Thaler 2003).

The existence of mispricing bring into question whether the option market leads the equity market. The evidence on the lead-lag relationship between the equity market and the option market is mixed. Cremers and Weinbaum (2010) uses differences in implied volatility ("volatility spread") of put and call options as a proxy for deviation from put-call parity. They find that both levels and changes of volatility spread can predict future stock returns. However, other studies do not find evidence that the option market leads the equity market (Stephan and Whaley 1990, Chan, Chung and Johnson, 1993).

The literature indicates that there is difference between the information content of the equity and option market. This study sheds further light into the relationship between the information in the equity and the option market. It also consolidates the findings about the lead-lag relationship of the prices in these two markets.

First, the results of this study show that divergence from put-call parity predicts future returns of the underlying security. The magnitude of divergence contains information about future stock returns. The results are robust over several strategies of portfolio rebalancing periods. I show that using divergence from put-call parity, it is possible to develop a trading strategy that generates positive excess returns. These excess returns persist over multiple holding periods. I find that the securities with the lowest divergence from put-call parity outperform securities with highest divergence by 37 basis points per trading day. The profits derived from divergence portfolios are not attributable to standard risk factors. After accounting for Fama-French (1993) and Carhart (1997) factors, excess returns still persist. I find positive and significant values of α for firms where the measure for divergence from put-call parity is positive. I find negative and significant values of α for firms where the measure of divergence from put-call parity is negative.

Second, this study examines how deviations from put-call parity are related to tail risk. Stocks with leptokurtic or fat-tailed distributions exhibit large negative price moves with high frequency. I find that divergence from put-call parity is positively correlated to occurrences of large negative moves. Results suggest that the stocks with the largest downside divergence from put call parity is more than twice as likely to experience a negative price jump compared to securities with the upside divergence. The probability of a large negative jump following the observation of a high degree of divergence is persistent for up to 12 days.

Third, this study allows me to infer the source divergence from put –call parity. To this end, I test two competing hypothesis. The informed trader hypothesis (Lee and Yi, 2001) states that put-call parity violations occur due to traders with insider information putting excess buying pressure on options. The overreaction hypothesis (Poteshman, 2001) states that option buyers speculate by putting excess buying pressure on options of the security in question. The findings of this study lend support to the informed trader hypothesis over the overreaction hypothesis.

This study contributes to the literature in multiple ways. Compared to previous studies, this study takes into account early exercise premiums of put and call options to calculate true divergence from the put-call parity identity. It is never optimal to early exercise an American call option on a non-dividend paying stock. However, if the underlying stock pays dividends, the call option prices on that stock include an early exercise premium. Previous research ignores early exercise premium of American call options when calculating implied stock price from options. The typical solution is to exclude all dividend paying options. This study improves upon existing methodology by considering call option early exercise premium and dividends to calculate implied stock prices.

This study consolidates the literature on the lead-lag relationship between equity and the option market. The results indicate that the option market leads the equity market. Also, this study is the first to address the relationship between divergence from put-call parity and large moves in the underlying security. The results suggest that tail events are correlated with the magnitude of divergence from put-call parity. Finally, this study compares the informed trader hypothesis to the overreaction hypothesis and lends support to the informed trader hypothesis.

The next section reviews the existing literature on price discovery in the option market.

2.2. Literature Review

Several recent studies attempt to explore the sources of divergence from put-call parity. One possible source for put-call parity violation is short-sale constraints. Put-call parity does not hold in the presence of short-sale constraints (Ofek et. al 2004, Lamont and Thaler 2003). Ofek, et. al. (2004) shows that there is a positive correlation between the magnitude of divergence from put-call parity and the magnitude of short-sale constraints. The violation is asymmetric in the direction of the short-sale constraint. They argue that in the presence of short-sale constraints, the pessimistic investor is unable to sell short. Therefore, the stock market only reflects the opinion of the optimistic trader. This induces an optimistic bias in the stock price that leads to overvaluations. They also state that divergence from put-call parity may result from the fact that the stock and options markets are segmented and the stock market is “less rational” than the options market. Finally, Ofek et. al. (2004) shows that firms with relatively expensive put options earn negative abnormal returns.

Ofek. et. al. (2004) also investigates predictability of returns from put-call parity violations. According to the authors, when there are no short-sale constraints, if stock is overvalued, the arbitrage strategy is to short the underlying stock, buy the call option and sell the put option. When a trader is able to do this successfully, there is no violation to put-call parity. However, when short-sale constraints are binding, put options become relatively expensive. This results in a violation of the put-call parity. If prices return to their fundamental values over time, it is expected that stocks with relatively expensive puts will earn lower returns. Ofek. et. al. (2004) examine average excess stock returns over the life of the option and find that a stock with put-call parity violation more than 1% experiences a -4.49% excess return over the life of the option. They also test predictability from put-call parity by constructing zero investment long-short portfolios. They form a long portfolio of industry returns, and a short portfolio of stocks that meet short sale constraints and put call parity violation criteria. This trading strategy yields positive excess returns and the returns are higher across quintiles formed on short sale constraints.

Battalio and Schultz (2006) find results contradictory to Ofek et. al.'s (2004) hypothesis. They find that short-sale constraints were not the cause of overpriced securities during the internet bubble of 1999. During that period investors could easily short internet stocks in the stock market or synthetically short using options in the option market. Their findings cast doubt on the finding that short-sale constraint is the only contributor to overpriced assets.

Battalio and Schultz (2006) also raise the concern that Ofek et. al.'s (2004) findings of a large number of put-call parity violations are due to an anomaly in the OptionMetrics database. OptionMetrics collects closing option prices from the option market with time-stamp of 4:02 PM. Whereas, trading in the New York Stock Exchange and the NASDAQ ceases at 4:00 PM. Ofek et. al. (2004) uses these data elements to calculate the violations of put-call parity. Battalio and Schultz (2006) show that most of the arbitrage opportunities identified by Ofek et. al. (2004) appears to exist only because of non-synchronous data. This data inconsistency is present in OptionMetrics prior to 2007.

A second possible source of divergence from put-call parity is information motivated trading. Informed investors can take advantage of financial leverage when they use options. However, only small investors use the options market as their primary trading venue (Lee and Yi 2001).

Roll, Schwartz and Subrahmanyam (2009) find that firms with higher options trading volume have higher Tobin's Q. They also find that option trading volume increases future firm profitability. They argue that more informed traders trade in the options market. This increases informational efficiency of the underlying asset. Increased informational efficiency increases firm's valuation. They also show that firm value is affected more strongly to option trading when there is greater information asymmetry.

Easly et. al. (1998) develops a measure known as the probability of informed trading (PIN). Using this measure, Cremers and Weinbaum (2010) demonstrates that stocks in the highest PIN groups earn the highest profits.

A third and final possibility is that the divergence from put-call parity occurs simply due to market imperfections. There may not be arbitrageurs to take advantage of divergences from put-call parity and as a result, the violation persists.

Recent literature addresses the issue of divergence from put-call parity and predictability of equity returns. Cremers and Weinbaum (2010) use differences in implied volatility ("volatility spread") of put and call option as a proxy for deviation from put-call parity. They find that both levels and changes of volatility spread can predict future stock returns. They demonstrate that predictability can occur on both long and short sides, which contradict the notion that violation results solely from short-sale constraints. Second, they point out that predictability results from informed trading.

One limitation of their study is that, their measure for deviation, the volatility spread, is a proxy for divergence from put-call parity. In contrast, I explicitly calculate the deviations from put-call parity by calculating differences between the cost of synthetic long and synthetic short positions using option market prices.

Goyal and Sarreto (2009) take a similar approach to examine predictability of option returns from implied volatility in the options market. They use differences in historical volatility and implied volatility to develop option portfolios. They then use a trading strategy using these portfolios to demonstrate predictability. The authors argue that options' implied volatilities decrease when investors underestimate the riskiness of a certain stock after periods of high returns. This last finding indicates that I might find momentum effects that lead to profitable trading strategies.

2.3. Option Implied Prices and Divergence from Put-Call Parity

2.3.1 Theoretical Background

I construct the following measure of divergence from put-call parity:

$$Divergence = \left(S^{b}_{synthetic} - S^{a}\right) - \left(S^{b} - S^{a}_{synthetic}\right)$$

where $S^{b}_{synthetic}$ is the cost of a synthetic short position, $S^{a}_{synthetic}$ is the cost of a synthetic long position, S^{a} and S^{b} are market bid and ask prices of the equity. The definition of the divergence measure implies that divergence can be interpreted as a measure of downward pressure in the option market. My measure explicitly calculates early exercise premiums for American put and call options using the methodology developed by Barone-Adesi and Whaley (1987). The next few sections discuss this methodology in detail.

2.3.2. Derivation of Implied Stock Price of American Options

The put call parity condition can be written as the following:

$$S = PV(K) + C - (P - EEP)$$

where S is the price of the underlying security, $PV(K)$ is the present value of strike price, C is the market price of call option, and P is the market price of the put option. Here EEP represents the early exercise premium on the American put option.

I also consider call option early exercise premium on dividend paying stocks. Since it is never optimal to exercise early on a non-dividend paying stock, I set call option early-exercise premium to zero for stocks that pay no dividends. For dividend paying options, I calculate the early exercise premium using the methodology developed by Barone-Adesi and Whaley (1987). For dividend paying stocks, the modified put-call parity condition is the following:

$$S = PV(K) + (C - EEP_{call}) - \left(P - EEP_{put}\right) + Dividend * e^{-rT}.$$

Barone-Adesi and Whaley (1987) defines call option prices through the following equations:

$$C(S,T) = c(S,T) + A_2\left(\frac{S}{S^*}\right)^{q_2} \quad if\ S < S^*$$

$$C(S,T) = S - X \qquad\qquad if\ S > S^*$$

where,

$$q_2 = \frac{1}{2}\left(-(N-1) + \sqrt{(N-1)^2 + \frac{4M}{K}}\right)$$

$$A_2 = \frac{S^*}{q_2}\left(1 - e^{(b-r)(T-t)}N\left(d1(S^*)\right)\right)$$

$$M = \frac{2r}{\sigma^2}$$

$$N = \frac{2b}{\sigma^2}$$

$$K(T) = 1 - e^{-r(T-t)}$$

and S^* solves the following equation:

$$S^* - X = c(S^*,T) + \frac{S^*}{q_2}\left(1 - e^{(b-r)(T-t)}N\left(d1(S^*)\right)\right).$$

Here $c(S,T)$ denotes the European call option price derived using Black-Scholes methodology, and b represents the continuous payout of the underlying stock.

2.3.3. Derivation of Early Exercise Premium

I follow the approach in Barone-Adesi and Whaley (1987) methodology to derive the early exercise premiums:

$$EEP = A_2 \left(\frac{S}{S^*}\right)^{q_2} \qquad if\ S < S^*$$

$$EEP = S - X - c(S,T) \quad if\ S => S^* .$$

Third, I calculate divergence from put-call parity.

2.3.4. Derivation of Divergence from PCP

The implied stock price from put-call parity is calculated as:

$$IS = Ke^{-rT} + (C - EEP_{call}) - \left(P - EEP_{put}\right) + dividend\ .$$

Previously I defined put-call parity as the following:

$$S = PV(K) + (C - EEP_{call}) - (P - EEP_{put})\ .$$

When the equality does not hold, I get violation of put-call parity.

It is more common that arbitrage opportunities arise when the stock is overpriced in the stock market. Consider the following equation:

$$S > PV(K) + (C - EEP_{call}) - (P - EEP_{put}) + Dividend * e^{-rT}.$$

In this situation, an arbitrageur can short the overpriced stock in the stock market, take a long position on a call option, take a short position on a put option, lend the present value of exercise price and lend the present value of the dividend to realize arbitrage profits. However, the arbitrageur faces several bid-ask spreads that limit the profitability of arbitrage strategy.

In order to carry out the operation described above, he receives the bid price of the shorted stock in the stock market. Simultaneously, he pays the ask price for the call option, receives the bid price for the put option and lends the value of the exercise price at the lending (bid) rate.

I call the latter part of this transaction a synthetic long. I define the synthetic long position as the following:

$$S^a_{synthetic} = (C^a - EEP_{call}) - \left(P^b - EEP_{put}\right) + Ke^{-r_bT} + Dividend * e^{-r_bT}.$$

Arbitrage profit can be made in this situation by going long the Synthetic Ask position and shorting the actual stock. So, the arbitrageur faces a negative cash flow of $S^a_{synthetic}$ and a positive cash flow of S^b.

I define the profit from going long the synthetic stock as "upside profit".

$$Upside\ profit = S^b - S^a_{synthetic}.$$

On the other hand, consider the situation where the following equation holds:

$$S < PV(K) + (C - EEP_{call}) - (P - EEP_{put})\ .$$

The arbitrageur could make a profit by shorting the right hand side of the equation. In this case the arbitrageur could buy the stock on the stock market. Simultaneously, he would sell a call option at the bid price, buy a put option at the ask price and borrow the present value of strike price at the borrowing (ask) rate.

I define the cost of this transaction as a synthetic bid:

$$S^b_{synthetic} = (C^b - EEP_{call}) - \left(P^a - EEP_{put}\right) + Ke^{-r_a T} + Dividend * e^{-r_a T}.$$

I define the profit obtained by buying the stock in the stock market and shorting the synthetic stock as "downside profit".

$$Downside\ profit = S^b_{synthetic} - S^a.$$

I refer to the measure put call parity violation as "divergence". I define it as the following:

$$Divergence = Downside\ profit - Upside\ profit$$

$$Divergence = \left(S^b_{synthetic} - S^a\right) - \left(S^b - S^a_{synthetic}\right).$$

When synthetic long is more costly, call options are relatively more expensive. So as divergence increases, I would expect future returns to decrease. Divergence can be loosely interpreted as a measure of relative downward pressure in the option market.

When a synthetic long position becomes relatively costly in comparison to a synthetic short position, it is possible that informed investors are exploiting positive news by going to the options market and bidding up the price of synthetic calls. In this case I expect to see positive abnormal returns on the underlying equity. Therefore, I predict that the higher the divergence, the lower the returns. Similarly, when a synthetic short position is relatively expensive, I expect negative abnormal returns. The divergence measure can therefore reflect market expectations of both informed and uninformed traders.

To further test the informed trader hypothesis, I analyze out-of-the-money (OTM), at-the-money (ATM) and in-the-money (ITM) options. OTM options offer the highest leverage to informed traders (Chakravarty et. al., 2004). If the results show that divergence has higher positive returns from an OTM subsample, then that will lend support to the informed trading hypothesis.

If divergence is a positive number, it means that the put pressure is dominating. In this case I would expect negative future returns. If divergence is negative, call pressure is dominating and I would expect positive future returns. However, if I assume prices are mean reverting, I would expect zero future returns over longer holding periods. If results fail to show long term reversion, it would be reasonable to conclude that the results are not consistent with the overreaction hypothesis.

2.3.5. Measurement of Tail Risk

To identify whether divergence can predict large movements, it is important to define tail risk first. I identify a tail event as a move that is expected only 1% of the time based on the historical distribution of the underlying security.

For the clarity of definition, I discuss the now popular Value-at-Risk or VaR measure first. VaR is the expected maximum loss given a certain confidence level (or probability level) and time horizon. VaR can be described as the quantile that corresponds to the maximum loss given a probability level.

Mathematically:

$$p = Prob(x > VaR) = \int_{VaR}^{\infty} f(x)dx$$

$$1 - p = Prob(x < VaR) = \int_{-\infty}^{VaR} f(x)dx$$

where x is the return of the security; VaR is the maximum loss (down move) given probability p, $f(x)$ in the probability density function of the security's return.

Figure B.1 shows the distribution of the S&P500 index. Figure B.1 overlays two distributions on top of the histogram. The first is the dark blue line, which is the non-parametric kernel distribution. The second is the fitted student's t-distribution, where the degrees of freedom has been calibrated to closely resemble the fat-tails. The dashed line shows the 99% VaR level for the return distribution of the S&P 500 index. The 99% VaR level is -3.56% from the fitted t-distribution. This means that 99% of the time, I would expect a one-day return to be higher than -3.56%. In other words, there is only a 1% probability that the return on S&P 500 will be lower than -3.56% in any given day. Any 1 day return lower than -3.56% qualifies as a breach of the 1-day, 99% VaR; and is considered as a tail event.

The VaR is also a function of time. For a given distribution $f(x)$ and a confidence level p, the VaR increases over time. A multi-period VaR is calculated simply by scaling the 1-period VaR by the square root of the time horizon.

The relationship between a 1 period VaR and a t-period VaR can be expressed as the following:

$$VaR_{[T\ period]} = VaR_{[1\ period]} * \sqrt{T}\ .$$

I define a tail event as a violation of the 99% VaR. Once I have calculated the 1 day VaR, I calculate 3, 6, 9, 12, 15 and 18 day VaR values to by using the equation above.

To estimate the VaR, I use 3 different methods.[1] The first is a non-parametric approach known as a historical simulation method. This does not assume a known functional form for the probability density function of the security. The second and third methods are parametric where I fit well known distributions to the empirical distributions of the security. The second method fits a

[1] See Duffie and Pan (1997) for details on various VaR methods

normal distribution to the 1-day returns of the underlying security. Equity return distributions often exhibit lepto-kurtosis (fat tails). To account for that, I also fit a t-distribution and calibrate the degrees of freedom parameter, so that the estimated probability density function not only has a known functional form, but also the fat-tails that resemble the empirical distribution.

2.3.6. Divergence and Time to Maturity

Ofek et. al. (2004) argues PCP violation should increase in the maturity of the option as the expected magnitude of reversion to fundamental value increases. An alternative "spread" hypothesis suggests that the longer the time to maturity, the larger the bid-ask spread. The larger bid-ask spread decreases the profit potential from option trades using these options. In this case, informed investor would not primarily rely on long term options to take advantage of their insider information. In this case violation should decrease in time to maturity. I test the two contending hypothesis.

2.4. Data

I obtain options data from OptionMetrics. OptionMetrics contains information on US equity and index options. I collect daily closing bid and ask prices for all options. The dataset also contains implied volatilities and option Greeks on all put and call options. The sample period used in this study is from January 2004 to December 2009. To find the effectiveness of signals obtained from the option market I form equity portfolios based on option market signals. For that, I retrieve daily equity data from CRSP. The daily equity data contains dividend adjusted daily returns. I also retrieve Fama-French risk factors from Kenneth French's website.

For stock portfolio analysis, the final dataset contains a time series of 1459 daily cross-sections ranging from 2004-01-02 to 2009-10-30. There are 4397 unique CUSIPs in the dataset. The final dataset contains 3,475,128 daily firm level observations.

A part of the sample overlaps with the time period where stock and option quotes are non-synchronous. From 2007 to the end of the sample, the data is free of this issue. In a future extension to this study, I plan to test whether the non-synchronous data issue creates material differences in the results prior to and after 2007.

2.5. Results

Looking at the distribution of the measure of divergence it becomes apparent that the distribution is marginally skewed to the right. This indicates that within the sample, put option pressure is observed more frequently compared to call options.

2.5.1. Divergence and Future Equity Returns

In order to test predictability of future equity returns from divergence, I rank all equities into ten portfolios on the basis of divergence. For the first test, the portfolios are rebalanced everyday based on the observed divergence of all equities. Next, I calculate equal weighted daily average returns for each cross section in the sample. I also calculate the returns of a hedge portfolio that is long equities with the lowest divergence and short equities with the highest divergence for each trading day. Finally, I calculate the average returns of each portfolio over the entire time series. I present the results of this analysis in table A.1.

Table A.1 ranks the equities into ten equal deciles by divergence. The equities with lowest divergence are assigned to portfolio 1, while the equities with the highest divergence are assigned to portfolio 10. From the definition of the divergence measure it is clear that portfolio 1 is dominated by upside pressure while portfolio 10 is dominated by downside pressure.

In table A.1, returns are monotonically decreasing with divergence. The decile 1 portfolio earns a positive return of .21% daily return on average. The decile 10 portfolio yields an average daily return of -.15%. A hedge portfolio trading strategy involving a short position in decile 10 (low/upside divergence portfolio) and a short position in decile 1 (high/downside divergence portfolio) earns an excess return of 0.37% daily. The t-stat on the hedge portfolio return is 18.86, indicating that the results are highly statistically significant. This is equivalent to a continuously compounded monthly return of a 8.07%. [2]

The results in table A.1 show that divergence has a high degree of predictability about the future returns of a stock. This lends support to the hypothesis that divergence from put-call parity predicts future movements of the underlying. These high returns from trading strategies indicate that there is a high degree of predictability in divergence from put-call parity.

2.5.2. Portfolio Performance over Multiple Holding Periods

It is possible that downside (high) divergence occurs only due to a temporal shift in demand for stock and options. In this case, divergence should quickly correct and approach zero. Quick corrections would indicate that markets are fairly efficient. In this case I would not expect any persistence in the direction of the movement of the underlying security after portfolios have been formed on the observed divergence measure. This can suggest that divergence from put-call parity is a function of overreaction of market participants.

On the other hand, if post-formation returns persist over a longer time horizon, it would suggest that divergence is correlated with some market participants correctly predicting the future direction of the underlying. If option market participants have non-public information, they can buy OTM options to achieve high leverage. High pressure buying would drive up the cost of synthetic positions and the underlying would follow.

Table A.2 shows divergence and equity returns over a 3 day holding period. The lowest divergence portfolio earns a 3-day cumulative return of 30 basis points, 9 basis points higher than a single day holding period. The highest divergence portfolio, earns a 3-day cumulative return of -18 basis points, 3 basis points lower than a single day holding period. Both high divergence and low divergence portfolio moves over 3 days are larger in magnitude than the 1 day move. The return on a hedge portfolio that is long the low divergence portfolio and is short the high divergence portfolio earns a cumulative return of 48 basis points over the 3 day holding period. The return on the

[2] I assume that there are 252 trading days in a year and 21 trading days in a month.

portfolio is highly significant. This persistence in the movement of the underlying lends support to the informed trading hypothesis over the investor overreaction hypothesis.

To further test the hypotheses, I construct portfolios and calculate the returns over 3, 6, 9, 12, 15 and 18 day holding periods, in addition to the 1 and 3 day holding periods. Table A.3 shows the cumulative return on the hedge portfolios that are long low divergence portfolios and short high divergence portfolios. I see the hedge portfolio returns increase monotonically with holding period. Over the span of 18 days after formation the hedge portfolio earns 1.2%. The hedge returns are highly statistically significant at every holding period.

In table A.4, I elaborate the returns on all portfolios formed over divergence for all holding periods. For all holding periods, highest divergence portfolios earn a negative return.

Figure B.2 shows that the highest return is realized with the longest holding period and the lowest return is also realized with the longest holding period. Returns are decreasing over the divergence axis for all holding periods. The cumulative returns on the extreme divergence ranked portfolios become further apart with longer holding periods. These observations provide evidence of persistence of return predictability from divergence.

2.5.3. Portfolio Performance over Time

The magnitude of divergence is time varying in nature. When market moves are more volatile, divergence from put call-parity violations are the highest.

Figure B.3 shows the divergence measure over the entire time series for the extreme divergence deciles. The solid line represents average level of divergence for the portfolio with the lowest divergence (upside pressure). The dashed line represents the average divergence measure with the highest level of divergence (downside pressure). All through the time series, decile 10 is positive and decile 1 is negative. This is consistent with the interpretation of divergence as downward pressure. In addition to that, the existence of high downside divergence (i.e. upward pressure) is consistent with the hypothesis that divergence from put-call parity cannot be explained by short-sale constraints (Cremers and Weinbaum, 2008).

An important observation is that upside and downside divergence reaches the peak around the height of the 2008-2009 financial crisis, coinciding with the collapse of Lehman Brothers.

I find that predictability from divergence is time varying in nature. Figure B.4 show the returns of extreme decile divergence portfolios. The solid line represents lowest divergence and the dashed line represents the highest divergence. Across the entire time series, average daily returns on the lowest divergence portfolio were higher than the highest divergence portfolio. The dashed line never crosses over the solid line. This means that a long-short strategy always made a non-negative return over the entire time series. The difference between the average daily returns of the extreme deciles represent the cross sectional average daily return of the hedge portfolio.

Figure B.5 shows the cross-sectional average daily returns of the hedge portfolio that is short decile 10 (high divergence) and long decile 1 (low divergence). The hedge portfolio earns a negative return only at the very end of the sample. For the rest of the sample the hedge portfolio persistently earns positive daily average returns. During turbulent market conditions, long-short hedge portfolios formed on divergence perform very well. The financial crisis period exhibits the highest returns. The highest average daily returns are around 1.25% near the time of the collapse of the Lehman Brothers.

2.5.4. Divergence and Tail Risk

The predictability of tail events from divergence is another way to test the informed trader hypothesis. If large moves are preceded by high divergence (excessive downward pressure), it is possible that the high value of divergence is attributable to OTM option purchases by option traders with a high degree of conviction. Excessive downward pressure is exerted in the option market when option traders anticipate large downward moves and purchase out of the money put options. A large increase in tail events at the highest divergence level, will lend support to the informed trader hypothesis.

To test whether divergence can predict tail risk, I calculate the number of times the 99% VaR is violated for each divergence portfolio.

Table A.5 shows divergence and the frequency of the 99% tail violation over the entire sample. The tail violations are measured using a t-distribution in table A.5. Tail violations are reported over multiple holding periods. To calculate tail violations for multiple holding periods, I compare post-formation T-period cumulative returns with $VaR_{1\ day} * \sqrt{T}$.

For all holding periods, the tail violations have the highest frequency in decile 10. The mean divergence in decile 9 is .81, and the mean divergence in decile 10 is 2.77. That large increase in the divergence between the two deciles shows that the downward pressure is much more severe in decile 10 than rest of the sample. I observe a large increase in the frequency of tail violations from decile 9 to decile 10. If divergence from put-call parity is consistent with the investor overreaction hypothesis, large moves would not follow a high degree of divergence. If divergence is correlated with overreaction, the forces of arbitrage would correct the divergence and the underlying security would experience a small downward move. If overreaction is truly the case, it is possible that average daily returns can increase with divergence – however, tail violations will not exhibit any correlations with divergence. Table A.5 exhibits a pattern of increasing tail violations with divergence. This observation is not consistent with the overreaction hypothesis.

Table A.6 shows the frequency of tail violations where a normal distribution is fitted to the empirical distribution of equity returns, over multiple holding periods across all divergence portfolios. Table A.6 exhibits a similar pattern of increasing tail violations with divergence. Decile 10 has the highest frequency of tail violation for all holding periods. Results in table A.5 and table A.6 are not consistent with the overreaction hypothesis.

Figure B.6 shows that one day tail violations are highest in the highest divergence decile. Regardless of whether non-parametric (historical simulation), normal, or t-distribution tail violation is used, this pattern is persistent.

Figure B.7 shows 3-day tail violations under the 3 distributions. The pattern is persistent and similar to figure B.6.

2.5.5. Risk Adjusted Returns

For the rest of this study, I restrict the analysis to a more recent subsample to verify the dynamics of divergence after the collapse of 2008. This subsample runs from April of 2009 to October of 2009. This subsample is also free of any issues related to non-synchronous quotes.

An alternative explanation for the varying returns on divergence deciles is that the underlying assets with high divergence from put-call parity are fundamentally riskier. The higher returns on these assets are therefore simply compensation for higher risk.

In order to test that the results are not merely driven by risk-varying characteristic of the underlying assets, I use Fama-French (1993) three factor model and Carhart (1997) four factor models. Table A.7 and table A.8 present the results of the 3 factor and 4 factor regressions respectively.

Table A.7 presents 3 different regression results. Regression (1) uses the entire subsample. Regression (2) uses only observations where divergence is negative. For stocks in this category, there should be more upside pressure than downside pressure. So, I expect that firms in this sample to experience positive returns. Regression (3) uses only the subsample of observations where divergence is positive. As discussed earlier, positive divergence implies that downside pressure is higher than the upside pressure. Regression (3) results exhibit negative returns on high divergence securities.

The results from table A.7, verify my claim that the higher returns across divergence portfolios are not due to risk varying characteristic of the underlying firm. In regression (1) the full sample α is .00252 and it is statistically significant. For the subsample with positive divergence (regression 2) I observe an α of positive 63 basis point (.63%). This value is not only statistically significant but also very high in magnitude compared to the full sample α. Finally regression (3) has a negative and significant α of negative 81 basis points (-.81%).

These results coincide with my expectations. The results together imply that after controlling for systematic risk, size and value risk factors, firms with positive divergence have negative abnormal returns. At the same time firms with negative divergence have positive abnormal returns. The regression results indicate that the abnormal returns are not due to risk varying characteristics of the firm. The results further suggest that the positive returns are likely to be correlated with informed trading.

One particularly interesting observation from regression (3) is that the coefficient on the HML factor is insignificant for negative divergence stocks. The positive and significant coefficient on HML for both specifications (1) and (3) indicate that value firms earn higher returns in the sample. It is interesting that for negative divergence firms, HML has no effect on return. This indicates that both value and growth firms earn similar returns on firms with negative divergence.

Next, I test whether momentum may have any effect on the returns. I run a similar set of regressions in table A.7, but I now use the Carhart (1997) four factor model. Table A.8 presents the results of this model.

Again, table A.8 shows that, α is positive and significant for negative divergence and negative and significant for positive divergence. On average, negative divergence securities earn positive 58 basis points of risk adjusted returns and positive divergence equities earn negative 82 basis points. These results again confirm my hypothesis.

2.5.6. Other measures of Divergence

To make sure the results are robust, I construct the divergence measure using options with different levels of moneyness.

Table A.9 reports the summary statistics of the divergence measures. Panel A shows the summary statistics of divergence when divergence is derived only from ATM options, panel B shows results when divergence is derived from in the money options and panel C shows results when divergence is derived from out of the money options.

The divergences from multiple levels of moneyness and maturity are different. Divergence measured using longer term options show a higher degree of variability. In terms of moneyness, at-the-money options show the highest variability. Divergence is monotonously increasing from very short term options to long term options. Since longer term options are subject to a higher degree of divergence, in the next sections, I investigate whether constructing the divergence measure from long term options yield higher returns from portfolio strategies.

2.5.7. Portfolio Performance using Various Measures of Divergence

Table A.10 shows returns from portfolios constructed using options with several times to maturity and moneyness levels.

Panel A shows returns from portfolios formed on divergence constructed using at-the-money options. Panel B shows returns from portfolios formed on divergence measured from in-the-money options. Panel C shows returns from portfolios formed on divergence measured from out-of-the-money options.

Table A.11 reports the long-short hedge portfolio returns for the portfolios shown in Table A.10.

The performance of the hedge portfolios are best when divergence in constructed using out-of-the-money options. This finding again lends support to the informed trader hypothesis. Downward pressure should be observed first in out-of-the-money options when the informed investor wants to use high leverage. Among the hedge-portfolios constructed using OTM option based divergence, the hedge portfolio that uses long term OTM option based divergence, performs the best.

2.6. Conclusion

I find that option market information can be used to predict future returns. I construct a measure of divergence from put-call parity, which is easily interpreted as a measure of downward pressure in the option market. The downward (upward) pressure is subsequently followed by a down (up) move in the underlying equity. This dynamic of the option market leading the equity market is robust across the entire time-series in the sample and is consistent on a risk-adjusted basis. Divergence is also predictive of large down moves (tail events).

Return predictability can be explained by several competing hypothesis. The market could be segmented and options traders maybe more rational, therefore leading to price discovery in the options market. Another possible hypothesis that can explain predictability is informed trading in the options market. A third hypothesis suggests that predictability occurs due to investor over-reaction. Finally, there is a possibility that markets are simply imperfect and divergence occurs due to this imperfection. The findings of this study support the informed trader hypothesis, over the investor overreaction hypothesis.

Future extensions of this study will include further tests to verify that the returns on divergence portfolios are not due to risk varying characteristics of the equities. I plan to control for firm specific risk factors and test whether the abnormal returns persist. I also plan to investigate whether issues related to non-synchronous data have significant impact on the findings of this study.

CHAPTER 3

SEGMENTATION OF EQUITY AND OPTIONS MARKETS

3.1. Introduction

Investors with negative information about a stock can use short-sale and (or) options to exploit their private information. But participants in the stock and option market may not react to the same set of negative information in the same way. Ofek et. al. (2004) argue that if markets are segmented and marginal investors across the stock and option markets are different, then prices in these markets may also differ. They state that in the absence of some friction, such as short-sale constraints, the price deviation is not rational. They also state that equity market participants are "less-rational" than option market participants.

In this paper, I address whether equity market participants are truly less-rational, by examining the predictability of future stock returns using signals obtained from equity and options markets. I find that option market based signals have better stock return predictability than short-sale based signals. Short-selling based signals are not reliable predictors of future returns. More interestingly, when short-sellers assume positions contrary to option market based signals, the stock earns positive returns, generating losses for short-sellers. In contrast, option market based signals retain their high degree of predictability after I control for short-sale based signals. Another explanation for short-seller underperformance is that short-sellers are slower to react to information compared to option market participants. The results suggest that the predictability of short-sell signals diminish after one-trading day. This finding indicates that the equity market lags the option market. These findings are consistent with the notion that stock and options markets are segmented and support the hypothesis that short sellers are less rational than the option market participants.

The unique contribution of this study to the current literature is threefold. First, this study shows that the information sets in the stock and option markets are not the same. Option market measures are stronger predictors of future equity returns than the short-sale measure. I show that the short sellers make profits only when their convictions coincide with option market traders'. Short-sellers are unable to make profits when they assume positions contrary to option market based signals. These results support the hypothesis that equity and option markets are segmented and short-sellers are less-rational than option traders.

Second, I find that there is synergy value in inter-acting multiple option market signals. I find that a long-short strategy that uses bi-variate portfolios formed on skewness and implied price ratio outperform a long-short strategy that uses bi-variate portfolios on short ratio and one of the option signals (either skewness or implied price ratio). This finding may be particularly valuable to practitioners since it indicates that both option implied price ratio and skewness contribute unique information that can be used to construct profitable trading strategies.

Third, most recent studies concentrate on long horizon data, such as monthly data, to test predictability (Cremers and Weinbaum, 2010; Xing et. al. 2010; Yan 2011). I think it unlikely that information discrepancies between markets persist for a 30-day long horizon. Tests on predictability using such long-horizon data may get affected by the risk factors associated with the underlying equity. In contrast to the previous studies, I use daily data to test the speed of information incorporation in stock and equity markets when information flow is fast.

The next section discusses the literature relevant to this chapter.

3.2 Literature Review

Stock return predictability has been documented in both the short-sale market and the option market. Investors with negative information about a stock can use short-sale and (or) options to exploit their private information. In the short-sale market, the stocks with high short-sale activities underperform those with low short-sale activities (Asquith et. al., 2005, Dechow et. al., 2001). Desai et. al. (2002) shows that high short interest among NASDAQ stocks signal negative information about the stock. These stocks subsequently earn negative returns. Thus, the portfolio consisting of short positions in high short-sale stocks and long positions in low short-sale stocks can generate significant abnormal returns. Short-selling also precedes events that reveal new information about the stock. Christophe, Ferri and Hsieh (2010) show that abnormal short-selling occurs on days leading to analyst downgrades. Christophe, Ferri and Angel (2004) find evidence that pre-announcement abnormal short selling predicts the price reaction once earnings are revealed. They also find that the predictability is stronger for firms without put options, implying that informed traders resort to the short-sale market to exploit private information only when they cannot buy put options. This finding implies that more private information is revealed in the option market compared to short-selling market when both buying put options and short-selling is viable. Another strand of literature demonstrates overreaction of equity market participants. Debondt and Thaler (1985, 1987) show, extreme past losers outperform extreme past winners over a period of five years after the formation of portfolios. They argue that investors overreact to recent past performance of stocks, bid up the winners and oversell the losers. This overreaction results in mispricing of equities, and a contrarian strategy that buys the losers and sells the winners can generate significant abnormal returns. I conjecture that short sellers may also be subject to such overreactions.

In the options market, several recent papers also show that the trading signals extracted from the options predict the future stock returns. Ofek et. al. (2004) shows that firms with relatively expensive put options earn negative abnormal returns. Xing, Zhang and Zhao (2010) show that the magnitude of the slope of the implied volatility smiles in individual equity options has a negative relationship with future stock returns. This study investigates whether or not it is the same set of negative information driving the short-sale activities and option trading signals.

Similar to the previous studies regarding the stock short-sale, the short-sale activities are measured as the short-sale volume divided by the stock trading volume. Regarding option signals, I utilize two distinct measures—implied volatility smirk and option implied price ratio, to test the predictability of future returns from option market.

Bates (1991) shows that index options across different exercise prices can provide an indication of an oncoming crash. Investors' concerns about a future negative jump are reflected in the options market as put option prices increase and call option prices decline. Particularly, out-of-the-money put options increase in value compared to at-the-money call options. As a result, the implied volatility of these OTM put options also increase in comparison to ATM call options. This particular phenomenon indicates that the implied volatility smirk is steepest when there is a high probability of a negative price jump. Xing, Zhang and Zhao (2010) show that implied volatility smiles are prevalent in individual equity stock options. They find that implied volatility smirks can predict stock returns, and these returns are persistent for at least six months. They also show that stocks with the highest slope experience negative future earnings shocks. They argue that informed traders who have knowledge of adverse news about the firm's fundamentals are the likely reason for the pronounced volatility smirk.

Cremers and Weinbaum (2010) also use differences in implied volatility ("volatility spread") to measure the deviation from put-call parity. They find that both levels and changes of volatility spread can predict future stock returns. Cremers and Weinbaum (2010) also demonstrate that predictability can occur on both long and short sides, which contradicts the notion that the violation of put-call parity results solely from short sale constraint (contrary to Ofek et al., 2004). In addition, they point out that predictability results from informed trading. Using a measure known as the PIN (Probability of informed trading) they demonstrate that high PIN groups earn the highest profits. The measure of skewness is closer to the one described in Xing, Zhang and Zhao (2010).

Ofek et. al. (2004) finds that violations of put-call parity are strongly related to short-sale constraints. However, they also find that violations of put-call parity are large both in number and magnitude during periods of mispricing. They indicate that this could be attributable to segmented stock and option markets.

3.3. Data and Methodology

I obtain daily option data from the OptionMetrics database. This dataset contains daily closing option prices, implied volatilities, open interest and volume on all exchange listed call and put options. The implied volatility reported in OptionMetrics is calculated using a binomial tree approach which takes into account dividend payments and possibility of early exercise for American options. To ensure that options have sufficient liquidity, I consider only options that have between 10 and 60 days to maturity. By focusing on short-term options, I circumvent issues related to volatility term structure.

I match daily option data with daily stock return data from CRSP. I also obtain daily closing short sale volume data for all NYSE stocks. In this study, I only use firms with short sale data, so the measure of option implied price ratio is not subject to short-sale constraints.

3.3.1. Calculating Volatility Skew

The first option based measure is the slope of the implied volatility smirk. Several studies discuss the information content of implied volatility smirks.

To calculate volatility skew, I first categorize:

$$\text{Options as ATM when } -0.1 < \ln\left(\frac{S}{K}\right) < 0.1$$

$$\text{Options as OTM when } -0.3 < \ln\left(\frac{S}{K}\right) < -0.1$$

Following the approach of Xing, Zhang and Zhao (2010), I define volatility spread as the difference between implied volatilities of OTM puts and implied volatilities of ATM calls.

$$VS_{i,t} = IV_{i,t}^{OTM\_PUT} - IV_{i,t}^{ATM\_CALL}.$$

When there are more than one ATM and OTM options for one stock in a given day, I calculate the average IV for all options that fall in that category. I then calculate the difference between these two averages to calculate the volatility skew measure.

3.3.2. Calculating Option Implied Stock Prices and Relative Mispricing

The second option based measure is option implied price ratio.

$$R = 100 * \log\left(\frac{S}{IS}\right).$$

Here S represents the stock price and IS represents the stock price implied by options. The implied stock price is obtained from the well-known no arbitrage equilibrium condition of put-call parity. I interpret the ratio R as a proxy of relative overvaluation in the equity market. This ratio also measures the deviation from put-call parity.

Unlike the volatility skew measure, I derive the implied stock price from options along the entire spectrum of strike prices. I improve upon existing methodology by considering the call option early exercise premium and dividends to calculate implied stock prices.

The most basic form of the put-call parity condition can be written as the following:

$$S = PV(K) + C - (P - EEP).$$

Here EEP is the early exercise premium on the American put option and $PV(K)$ represents the discounted present value of the strike price. For dividend paying stocks, I also consider early exercise premium of call options. Since it is never optimal to exercise early on a non-dividend paying stock, I set call option EEP to zero in the absence of dividends. For dividend paying options, I calculate the EEP as shown in Barone-Adesi and Whaley (1987). The modified put-call parity condition for American call option is the following:

$$S = PV(K) + (C - EEP_{call}) - (P - EEP_{put}).$$

I use the Barone-Adesi and Whaley (1987) method of pricing American call and put options to calculate implied stock prices from option market data.

For dividend paying options, the implied price from put-call parity is calculated as:

$$IS = Ke^{-rT} + (C - EEP_{call}) - (P - EEP_{put}) + dividend\ .$$

Finally, as a measure of mispricing in the equity market I create a simple ratio that represents relative overvaluation in the equity market.

$$R = 100 * \ln\left(\frac{S}{IS}\right).$$

3.3.3. Short Sale Volume Ratio

I take the ratio of short selling volume to buying volume at the end of each trading day to measure equity market signals. High short volume ratio (SVR) indicates that traders in the equity market anticipate bad news about the firm's fundamentals.

3.3.4. Summary Statistics

In table A.12, the implied stock-based measure, R is monotonically increasing in VS. Relative SVR is decreasing in VS. VS contains some information that is consistent with SVR. This preliminary finding indicates that informed trading might take place in the equity market as well as the option market. Later, I compare the extent of future return predictability using both of these measures. The next column displays the average realized historical volatility across the VS deciles. I find that the highest volatility decile, the one facing the highest probability of a negative price jump, has the lowest historical volatility. This may seem counterintuitive at first glance, but it is possible that this is due to the fact that after a period of consolidation, stocks become more susceptible to a large price jump. For example, investors can become weary of a firm’s upside potential following a stable price run up. VS is a forward looking measure, so investor caution is reflected in the option prices. Another possibility is that, negative price jumps are more likely to occur following a convergence of opinions. For example, once beliefs about the firm converge, as reflected in historical volatility (HV), the possibility of a down jump increases. In these situations, new information would disrupt prices more than would otherwise. The last column of the table shows that difference of opinion decreases from decile 1 of through decile 9. Table A.12 shows a significant jump in differences in opinion (DIFOPN) from decile 9 to decile 10. This indicates that a portfolio's probability of negative price jump increases when opinions converge. The likelihood of a negative price jump is highest when HV is low and DIFOPN is high. Preliminary evidence suggests that low historical volatility is correlated with likelihood of a negative price jump.

I report summary statistics of relevant variables over deciles formed on the relative overvaluation variable R in table A.13. R can also be viewed as a deviation from the equilibrium relationship of put call parity. A negative R indicates that a synthetic long position in the option market is more expensive than holding the underlying stock. For the equilibrium relationship to hold, the stock price must rise. Similarly, a positive value of R in the stock market indicates that the synthetic position is relatively cheaper. In order for put-call parity to hold, the stock price must decrease. From the first column of table A.13, deciles 1 through 3 have a negative average value of R, while it is positive for deciles 4 through 10. Therefore, the first three deciles exhibit relative undervaluation in the equity market and the next 7 deciles correspond to relative overvaluation in the equity market. In the next column, while VS is increasing in R, the relationship is not strictly monotonic. I conjecture there might be information embedded in VS and R that are orthogonal to each other.[3] Short volume ratio is also increasing in R, albeit with a decline from decile 9 to decile 10. Thus, when stock prices are highly overvalued compared to implied stock prices, the SVR is not high enough. This again indicates the lagging nature of the equity market. In contrast to table A.12, HV is increasing in R. This indicates that the most overvalued stocks have higher past volatility.

Next, I look at mean values of the relevant variables across deciles formed on SVR. It is interesting to note that there is no monotonic pattern of average VS or R across the SVR deciles. VS exhibits an 'u-shaped' pattern over the deciles of VS. In fact, the lowest short volume decile corresponds to the highest VS. This indicates that what the equity market perceives to be safest (short volume of only 12%), is likely to have the largest probability of a large decline (a VS of .067) according to the option market signal. The contradictory nature of information in stock and equity

[3] To further analyze this issue I later form portfolios by double sorting stocks on the basis of VS and R in table 5

markets is striking. I also note that, historical volatility is increasing in SVR. This pattern is more consistent with R than with VS, which exhibits a decrease in HV across it's deciles. The lack of any monotonic pattern in either of the option based measures across deciles of SVR suggests that the information content of measures formed these two different markets should be distinct.

3.4. Equity Return Predictability from Option Market and Equity Market Signals

To test the predictability of the option-based measures, I rank stocks at the end of each trading day into deciles. I form equally weighted portfolios for stocks in each decile. These portfolios are held for 1 day before they are rebalanced.

3.4.1. Profitability from Univariate Investment Strategies

3.4.1.1. Predictability from VS

Table A.15 reports returns on portfolios formed on VS. I find that the average daily return decreases from .16% to -.11% from low VS to high VS. This is consistent with the hypothesis that stocks with higher VS have higher probability of experiencing a negative price jump. A zero-investment portfolio that assumes a long position on the lowest VS decile and assumes a short position on the highest VS decile earns an average daily return of .277% over the sample period. The corresponding continuously compounded annual average return is 101.2%. Consistent with Xing et al. (2010), I find that there is a high degree of predictability of future returns from VS. This result indicates that any insider information is reflected in the option market first.

3.4.1.2. Predictability from R

As discussed earlier, higher (lower) values of R correspond to overvaluation (undervaluation) of stocks in the equity market relative to the option market. If the option market indeed leads the stock market, stock prices should adjust to reflect the implied values of equity in the options market. If the adjustment process takes place in the equity market, relatively overvalued equities in the stock market should decline and relatively undervalued stocks in the equity market should increase in price. Subsequently, the portfolios formed on lower values of R should see positive returns and portfolios formed on higher values of R should see negative returns. If the equity market prices do not adjust towards implied prices, portfolios formed on R will not exhibit any correlation between R and returns. Thus, portfolios formed on the basis of R provide a direct test of the hypothesis that the option market leads the equity market.

Table A.16 reports returns on portfolios formed on R. Average daily returns decrease monotonically from .13% to -.14% over deciles of R. Returns on the extreme deciles are highly significant. The zero investment hedge portfolio earns a daily average return of .276%, significant at a .01% level. This result implies that the option market leads the equity market. The stock price at period $t+1$ moves in the direction implied by synthetic prices in the option market in period t.

3.4.1.3. Predictability from Short Volume Ratio

Next, I focus on the equity market measure of negative news. At the end of each trading day, I rank stocks on the basis on SVR into deciles and form equally weighted portfolios for each decile. The portfolios are held for 1 day and rebalanced every trading day based on SVR. Table A.17 shows that the average daily returns decline monotonically from decile 1 to decile 5. For decile 6 through 10, the returns on the portfolios are not monotonic and statistically insignificant. The time-series average return of the hedge portfolio is nearly .10% and is statistically significant. Although, I find predictability in future returns from SVR, it pales in comparison to the predictability from option market based measures. Strict monotonicity across deciles is also lost on the portfolios formed on SVR. The equities with highest SVR earn statistically insignificant returns. Stocks that are subject to high short selling in the equity market may not see large negative price moves. The traders who short these stocks may be too late to take advantage of negative information. It is also interesting to note that the statistical significance of the portfolio returns for the highest deciles of short-selling are the lowest. This indicates that the higher the short-sellers conviction, the lower the reliability of the signal obtained from short-selling. Decile 10, which represents extreme short-selling, does not earn any statistically significant return. The behavior of shorting stocks that subsequently do not go down is inconsistent with rationality. This is preliminary findings support the notion that short sellers are not rational.

The univariate tests reveal the superiority of option market based measures as predictors of future returns.

3.4.2. Profitability from Bi-variate Investment Strategies

To test the performance of option based measures, I form two dimensional portfolios based on VS and R. I argue that since these two measures capture two different kinds of risk, a two-dimensional strategy that utilizes both these factors should generate even higher returns. In panel A of table A.18, I rank stocks first on the basis of VS. Then within each VS quintile, I rank stocks on the basis of R. Panel B reverses the order of sorting, so that the first sort is on R and the second sort is on VS. In both cases I notice that stocks with high overvaluation in the equity market (high R) and stocks with high probability of negative news (high VS) earn the lowest returns. In contrast, the low R, low VS portfolio earns the highest returns. This long-short hedge portfolio earns a daily average return of .47%.

To analyze whether high SVR embodies information not already in the options market data, I form two-dimensional portfolios. In table A.19, panel A, I report the returns across SVR quintiles controlled by VS. For the lowest two VS deciles, high SVR stocks earn lower returns than low SVR portfolios. However, for the highest VS quintiles, returns across SVR quintiles are not monotonic. SVR portfolio 5 has higher returns than SVR portfolio 4 within the highest two VS deciles. I conclude that the SVR effect is weak after controlling for VS. When VS is low, the option market signal dictates that there is low probability of a negative move. All quintiles in the low VS portfolio earn positive returns, including the high SVR portfolios. For example, consider the highest SVR portfolio within the lowest VS quintile, which represents contradictory signals about the direction of expected future price move. High SVR indicates the presence of short-sellers with high conviction that the stock will go down. However, this portfolio earns positive returns of .07%. The short sellers' conviction does not predict when it diverges from option market signals. This is consistent with the hypothesis that option market leads the stock market. The "less-rational" short-seller in the equity market cannot make profits unless his bet is consistent with rational option market indicators.

In table A.19, panel B, I reverse the order of sorting by sorting first on SVR and then sorting on VS. When I control by SVR, the predictability of VS is never interrupted. For all quintiles of SVR, returns monotonically decrease over VS quintiles. The 5th column of panel B represents High VS. Note that unlike High SVR, all five portfolios in high VS earn negative returns. These results in panels A and B confirm the lead-lag relationship between the equity and option market.

In table A.20, within each portfolio formed on R, returns do not decrease monotonically across quintiles of SVR. High SVR quintiles within Low R quintiles continue to earn positive returns, resulting in losses for less-rational short-sellers when they disagree with option market signals. In panel B, after controlling for SVR, returns decline monotonically over quintiles of R. All 5 portfolios with high R earn negative returns, confirming that the mispricing in equity market is corrected on the direction predicted by options regardless of what short-seller convictions about those stocks might be. These results again show that option based measures contain information not found in stock based measures.

To control for the risk varying characteristics of the equities, I report risk-adjusted returns for all the bi-variate portfolios in the in tables 3.12 through 3.17. The tables control for firm specific size, and book-to-market. The tables also report abnormal returns from Fama-French (1993) three factor and Carhart (1997) four factor models. The risk adjusted returns are consistent with the patterns observed in the raw return portfolios. The risk-adjusted returns lend further support to the market segmentation argument.

3.4.3. Speed of Information Incorporation

To test speed of adjustment from new information, I employ Fama-Macbeth regression analysis. For each cross-section, I test the predictability of signals lagged one, two and three days relative to return date. Columns 1, 2 and 3 of table A.21 display results for predictive regressions with 1 day-lagged, 2 day-lagged and 3-day lagged signals respectively. In all three regressions the once-lagged value of VS predicts negative future returns. This is consistent with the hypothesis that higher VS predicts high probability of negative news. Columns 2 and 3 show that two day and three day lagged VS actually signals an increase in future returns. This suggests that the option market operates quickly. If an informed insider takes a highly leveraged position using OTM puts in anticipation of negative news, he is likely to close his positions once the negative jump in the underlying stock takes place. Therefore VS would change the next day, and there would be a negative correlation between VS_t and VS_{t-1}.

My findings indicate that the changes in the underlying take place within 1 trading day. Once-lagged SVR also displays predictability, predicting negative returns. Columns 2 and 3 show that values of SVR, lagged 2 and 3 days, are statistically insignificant. This could be due to the fact that short-sellers who act upon "old-news" in an already lagging market are only subject to random moves in the stock price unrelated to the signal they receive. The results suggest a higher speed of information incorporation in the option market compared to the equity market.

The results suggest that information gets incorporated into the option market faster. The reason behind the faster incorporation of information warrants further research.

3.4.4. Information Asymmetry between Equity and Option Markets

To analyze the relationship between the information environments and option and equity market based signals, I run Fama-Macbeth regressions of difference in opinion on the option and equity market signals. Table A.22 shows that both R and SVR are positively correlated to difference in opinions. High difference in opinion is analogous to high information asymmetry and characterizes environments where insider trading is likely to occur. This result, in combination with results from the last table, suggests that information arrives first in the option market. Short-sellers notice the relative overvaluation in the equity market and assume short positions. It is also possible that short-sellers themselves have private information. However, the results suggest that the primary venue for insider trading is the options market. It is interesting to note that VS is negatively related to difference in opinions.

3.5. Conclusions

I find evidence that option market participants are more-rational than short-sellers. Short-sellers can only profit from their short-positions when their convictions line-up with the implied direction of stock price move from the option market.

The first set of tests compare the predictability of short-selling signals and option based signals. I form univariate decile portfolios on daily observed skewness and find that future return decreases monotonically with volatility skew. Next, I form univariate decile portfolios on implied option price ratio and again find that returns monotonically decrease across the portfolios. Lastly, I form portfolios on the basis of short volume ratio. Interestingly enough, I find that the highest short ratio portfolios exhibit the lowest levels of statistical significance. This implies that the higher the conviction of the short-seller, the lower the likelihood that the short seller can make any statistically significant gains. This is consistent with the notion that equity market participants overreact. This result provides preliminary evidence that short-sellers are irrational. If the information sets in the stock and option markets are exactly the same, it is intriguing to examine if there is synergy value by combining these two sets of information.

To test for existence of any synergy values, I create a bi-variate portfolio strategy based on signals from option market and short-selling. As a benchmark, I first construct portfolios based on the two option market signals, namely skewness and option implied price ratio and find that a long-short investment strategy earns an average daily return of .47%. Next, I construct portfolios based on skewness and short-selling and find that the profitability of the long-short strategy decreases to .29% daily. I also construct portfolios based on option implied price ratio and short-selling. The long-short investment strategy earns a raw return of .27% daily. The results show that although there is synergy value by combining option based signals, there is no gain from interacting option signals with short-selling signals. This finding is consistent with the hypothesis of market segmentation and the low quality of short selling signals.

In the case of segmented markets, information may arrive faster to one market than the other. If markets are truly segmented, I would observe that the persistence of predictability from the signals from the two markets should differ. Reliable signals should retain predictability while unreliable signals should lose predictability. To test this, I test the speed of information incorporation in the option and short-selling markets by testing the predictability of lagged signals from both markets. Contrary to prior studies that use long horizon data (see, i.e. Xing et al., 2010), the results of this study indicates that the predictability of lagged option based signals diminish quickly. Twice lagged option based signals exhibit patterns opposite of once lagged signals. Equity market based signals are insignificant beyond the first period. These findings suggest that the option market adjusts faster to information than the equity market. Option traders close their positions once the underlying stock has moved in the direction implied by the signal.

Univariate portfolios reveal that option market based measures are better predictors of future returns than equity market based measures. The equity market indicator, short volume ratio, loses predictability when short-selling activity is highest. Short-sellers in these cases are too late to take advantage of their information.

Bivariate portfolios show that the short volume ratio metric loses predictability in the highest quintiles, controlling for option market signals. When I control for the short-volume ratio, the option market measures retain full predictability. This indicates the leading nature of the option market. Regression results on lagged equity and option market signals suggest that the speed of information incorporation is faster in the option market.

CHAPTER 4

CASHING IN ON FEAR: IMPLIED JUMP RISK PREMIUM AND THE CROSS-SECTION OF OPTION RETURNS

4.1. Introduction

The slope of the implied volatility smile contains information that can predict future returns (e.g. Xing et al., 2010 and Yan, 2011). Yan (2011) shows that the predictability of asset returns from volatility skew results from the existence of negative jump risk. Risk-averse investors can purchase out-of-the-money (OTM hereafter) put options as insurance to protect themselves from large negative price jumps and eliminate their downside risk. The highly risk-averse investors are willing to pay irrationally high prices to purchase protection against large adverse price moves (Dumas et. al., 1998). The seller can also demand higher prices for selling such protection. Consequently, the higher price of OTM options are reflected in higher implied volatility for OTM put options.

I construct a measure of investor fear or crash-phobia by using the implied volatility of OTM and ATM options. Using option market prices and implied volatilities, I empirically estimate the fear premium associated with the underlying stock and subsequently test investor overreaction. The fear premium contains compensation for fear of a negative jump. I extract this irrational portion of jump risk, attributable to fear of a crash, from the implied volatility skew. Next, I show that a zero-cost trading strategy involving a short position in an option portfolio on stocks with high fear premiums and a long position in an option portfolio on stocks with low fear premium earn a monthly return of 4.95%. The results are robust with respect to market frictions and the strategy earns a monthly return of 4.41% net of all transactions costs.

This study contributes to the existing literature in three ways. First, I verify empirically the theoretical relationship between diffusive volatility and slope of the implied volatility smile. The results lend support to the theoretical findings presented in Yan (2011). Second, I demonstrate a model-free procedure to decompose the information content of the implied volatility smile. I estimate the fear premium from multiple measures of volatility skew. The fear premium represents irrational overreaction of investors fearing a crash.

Third, I demonstrate that higher fear premiums are associated with higher profits from selling put options. I also show that higher fear premiums are associated with lower profits from selling call options. The results on put options support the hypothesis that investors often purchase insurance out of irrational fear. The losses on selling call option portfolios during high crash fear indicate that once the irrational fear subsides, the call option writers suffers losses.

The option market lends itself to a natural experiment to test whether the risk premium that compensates investors for jump risk, is consistent with observed option prices. This study finds that often, the risk premiums implied by observed market prices are much higher than it should be under a rational framework. The irrational component of the risk premium is attributable to fear.

The methodology developed in this paper to estimate the fear premium can benefit academics and practitioners alike. Academics can use the fear premium to test theoretical hypotheses related to investor overreaction and other cognitive biases. Practitioners can use the fear premium to create profitable trading strategies.

Finally, this study consolidates recent findings in the literature on the information content of the volatility smile and extends the literature by decomposing the irrational component of jump risk.

4.2 Literature Review

One common volatility estimation method is the Black-Scholes implied volatility, which is obtained by inverting the Black-Scholes (1973) model. The Black-Scholes model makes a strong assumption that stock returns are normally distributed with known mean and variance. If this assumption holds, the implied volatility for options on the same underlying stock should be the same regardless of moneyness. It is well established that the implied volatility of underlying stocks changes with an option's moneyness. Implied volatilities estimated using the out-of-the-money and in-the-money (ITM hereafter) options are typically larger than the implied volatility estimated using ATM options, a characteristic that the Black Scholes model fails to explain.

Merton's (1976) Jump Diffusion model explains the implied volatility smile better than Black-Scholes. Based on the jump diffusion model, Yan (2011) derives the relationship between the local steepness of implied volatility smile and jump likelihood. According to Yan (2011), the difference between the implied volatility of the put option and the implied volatility of the call option captures the likelihood of a down jump.

I draw upon a second study to derive the fear premium measure. Xing et. al. (2010) calculates volatility skew as the difference between implied volatilities of OTM puts and implied volatilities of at-the-money (ATM hereafter) calls.[4]

$$VS_{i,t}^{LEFT} = IV_{i,t}^{OTM\_PUT} - IV_{i,t}^{ATM\_CALL} \quad (1)$$

I label this variable as $VS_{i,t}^{LEFT}$ because it measures the slope of the implied volatility smile to the left of the current spot price. Three distinct levels of information are embedded in the volatility skew (Pan (2002), Xing et. al. (2010)). First, the left-side slope of the implied volatility smile captures the likelihood of a negative price jump. Second, the skew contains information about the expected magnitude of the price jump. Third, it contains the premium that compensates investors for both the risk of a jump and the risk that the jump could be large. Pan (2002), Xing et. al. (2010) also argue that a high VS^{LEFT} value represents anticipation of bad news. A high VS^{LEFT} value can also reflect informed investor demand for OTM put options. It is possible that the third component of VS^{LEFT} contains information about investor overreaction to the possibility of a large

[4] Xing et. Al. define ATM options when $.95 < \frac{K}{S} < 1.05$ and OTM options when $.80 < \frac{K}{S} < .95$.

negative move. However, it is influenced by informed investor demand, investor risk aversion and/or any potential overreaction to the possibility of a large negative jump. The combinations of these factors make it difficult to extract investor overreaction or fear from this measure.

Yan (2011) argues that, in contrast to the Xing et al. (2010) measure, his measure simply proxies for the risk neutral portion of jump risk (under the probability measure $\mathbb{Q}$). Yan assumes that stock and option markets are efficient, investors are rational and slope reflects just jump risk. The magnitude of $VS_{i,t}^{LOCAL}$ does not indicate anticipation of bad news. He also shows that under the risk-neutral measure, $VS_{i,t}^{LOCAL}$ proxies for the intensity and magnitude of a downward jump. [5]

Xing et al.'s (2010) measure of the volatility skew captures the probability, the magnitude and the risk premium and/or other factors that compensate the investors under the real world probability measure . Yan's (2011) measure captures the probability and the magnitude, under the risk neutral probability measure.

Bollerslev and Todorov (2011) take a non-parametric approach to quantify investor fear. First, they decompose jump risk premium into two components, (1) Equity jump risk premium and (2) Variance jump risk premium. They decompose the variance risk premium further into parts associated with positive and negative jumps. Next, they show that the difference between the variance risk premium due to the probability of a down jump and the variance risk premium due to the probability of an up jump is not influenced by any temporal variation in jump intensities.[6] This difference is also interpreted as a direct measure of investor fears. I adopt a similar specification to quantify fear.

Bates (1991) examines S&P 500 futures options over 1985-1987. He shows that OTM puts, which function as crash insurance, were unusually expensive the year before the October 1987 crash. This indicates that the crash was anticipated. He argues that the high price of crash insurance

[5] Proposition (3) in Yan (2011) states that proxies for local steepness are proportional to the product of jump intensity and average stock jump size.
[2] The Bollerslev and Todorov (2011) framework is discussed further in section 3.

can be explained by a jump-diffusion process, when there is skewness in investors' subjective distributions on the underlying asset. Bates (1991) fits daily option price data to a jump-diffusion model and estimates jump parameters implicit in option prices. He states that the parameters estimated are "risk-neutral" parameters, and inference about the true parameters requires additional assumptions about the degree of risk-aversion. Jackwerth and Rubinstein (1996) also find a component in option prices that captures the possibility of rare extreme events.

Heston (1993) develops a stochastic volatility model that provides a closed form solution for an European call option price when the spot return is correlated with volatility. The Heston (1993) model fails to explain the fat-tails of stock return distributions (Andersen, Benzoni, and Lund, 1998) or the volatility smirk (Bakshi, Cao, and Chen, 1997; Bates, 2000). Bates (2000) extends Heston's (1993) model by including state-dependent price jumps (SVJ model). He finds that the option implied distribution of the underlying asset is negatively skewed after the crash of 1987. He argues that this skewness is due to a change in investors' aggregate risk aversion.

Pan (2002) uses the Bates' (2000) model to show that that the SVJ model explains option prices across varying degrees of moneyness and maturity. Fitting the Bates (2000) model to stock and option prices reveals that there exists a significant risk premium associated with volatility and jumps. The SVJ model also explains changes in the shape of the volatility smile over time. Pan (2002) also argues that volatility smiles result from investor fears of large negative price jumps. I apply a different strategy by adopting a model free approach to estimate the jump risk premium.

Extant research has explored investor irrationality in the option markets. Poteshman (2001) studies investor under and over reaction to changes in the variance of the underlying asset. He finds that option market investors under react to instantaneous changes in volatility of the underlying assets. However, these investors overreact to changes in the volatility of the underlying when volatility is trending in either direction. Poteshman and Serbin (2003) show that option market investors often exhibit irrational early exercise behavior. Investors exercise their options irrationally most often when the underlying stock price attains a 52 week high. This desire to protect profits is consistent with buying puts at irrationally high prices. If investors are willing to pay irrational prices for insurance, it would be irrational for the seller not to oblige (Lowenstein, 2000).

4.3. Theoretical Framework

Following Black-Scholes (1973), I begin by modeling stock prices as geometric Brownian motions:

$$dS_i = \mu_i S_i dt + \sigma_i S_i dW_i \tag{2}$$

where S_i is the stock price for the i-th asset, μ_i is the drift, σ_i is the diffusion (volatility); and W_i is a standard wiener process with $E[dW_i] = 0$ and $E[dW^2] = dt$.

The jump-diffusion model introduces discontinuity in the Brownian motion, where the price of the i-th stock follows the process:

$$dS_i = \left(\mu_i - \lambda_i \mu_{ji}\right) S_i dt + \sigma_i S_i dW_i + J_i dN_i \tag{3}$$

where J_i represents the size of the jump, and J_i has the log-normal distribution:

$$\ln(1 + J_i) \sim N\left(\ln\left(1 + \mu_{ji}\right) - \frac{1}{2}\sigma_{ji}^2, \sigma_{ji}^2\right)$$

and dN_i represents a Poisson process defined as:

$$dN_i = \begin{cases} 0 \; with \; probability \; 1 - \lambda dt \\ 1 \; with \; probability \; \lambda dt \end{cases}$$

This implies that $prob(dN_i = 1) = \lambda_i dt$, and λ_i is the intensity of Poisson process N_i. Here λ_i is the instantaneous probability of a jump occurrence.

From the distribution of J_i, μ_{ji} is the expected jump size, the term $\lambda_i \mu_{ji}$ adjusts the drift for average jump size. When the jumps are negative ($\mu_{ji} < 0$), the term $-\lambda_i \mu_{ji} > 0$, which represents a premium that compensates an investor for jump risk.

Yan (2011) suggests that the local steepness implied volatility smile near-the-money is proportional to the average jump size.

$$\left.\frac{\partial \sigma_i^{implied}(X, T)}{\partial X}\right|_{X=0} = \frac{\lambda_i \mu_{ji}}{\sigma_i} + O(T) \tag{4}$$

X represents the log-moneyness of the option and is defined as $ln\left(\frac{K}{S}\right)$. T represents the remaining time-to-maturity of the option. The left hand side of equation (4) is evaluated at $X = 0$, which indicates that the options are at-the-money. The slope of implied volatility is approximately proportional to the product of jump size and jump intensity. It is inversely proportional to the diffusive volatility of the process. Yan (2011) also suggests that proxies for slope of implied volatility smile from ATM options should be approximately proportional to the product of jump intensity and average stock jump size:

$$s_i \approx L_i \lambda_i \mu_{ji} \tag{5}$$

where L_i is a positive constant and $\lambda_i \mu_{ji}$ is the product of jump intensity and average stock jump size. Given the relationship described by equations (4) and (5), s_i should be proportional to the product of jump intensity and average jump size of the process. Following Yan (2011), I use VS^{LOCAL} as a proxy for the slope of implied volatility curve.

Bollerslev and Todorov (2011), show that large portion of equity and variance risk premium is compensation for large and rare events (i.e. jumps). They find that the portion of the risk premium attributable to jump and the fear of a jump are quite large and time-varying. Bollerslev and Todorov (2011), empirically estimates an investor fears index to capture the portion of risk premium attributable to the fear of a jump.

Bollerslev and Todorov (2011) express the dynamics of future price as the following:

$$\frac{dF_t}{F_t} = \alpha_t dt + \sigma_t dW_t + \int_R (e^x - 1)\, \tilde{\mu}(dt, dx) \tag{6}$$

$$\text{where, } \tilde{\mu}(dt, dx) = \mu(dt, dx) - v_t^{\mathbb{P}}(dx)dt$$

$v_t^{\mathbb{P}}(dx)dt$ denotes the compensator (stochastic intensity) for jumps for $v_t^{\mathbb{P}}(dx)$ being predictable under real world ($\mathbb{P}$) probability measures.

A critical assumption in their framework is that the temporal variation in the jump intensity is a linear function of the stochastic volatility. Next, $v_t^{\mathbb{P}}(dx)$, the measure for jump intensity, is modeled as a function of stochastic volatility:

$$v_t^{\mathbb{P}}(dx) = \left(\alpha_0^- 1_{\{x<0\}} + \alpha_0^+ 1_{\{x>0\}} + \left(\alpha_1^- 1_{\{x<0\}} + \alpha_1^+ 1_{\{x>0\}}\right)\sigma_t^2\right)\ v^{\mathbb{P}}(x)dx \tag{7}$$

where $v^{\mathbb{P}}(x)$ is a Levy density α_0^- and α_0^+ are free parameters.

Quadratic variation of the price process is

$$QV_{[t,T]} = \int_t^T \sigma_s^2 ds + \int_t^T \int_R x^2 \mu(ds, dx) \tag{8}$$

The compensation associated with the uncertainty about a temporal change in variance is the variance risk premium. The variance risk premium is modeled as the scaled difference between the expectation of the quadratic variation of the process under the $\mathbb{P}$ and $\mathbb{Q}$ measures. Here, $\mathbb{Q}$ represents the risk-neutral probability measure.

$$VRP_t = \frac{1}{T-t}\left(E_t^{\mathbb{P}}\left(QV_{[t,T]}\right) - E_t^{\mathbb{Q}}\left(QV_{[t,T]}\right)\right) \tag{9}$$

This can be broken into continuous (associated with the diffusive component) and discrete (associated with the jump components) parts

$$VRP_t^c = \frac{1}{T-t}\left(E_t^{\mathbb{P}}\left(\int_t^T \sigma_s^2 ds\right) - E_t^{\mathbb{Q}}\left(\int_t^T \sigma_s^2 ds\right)\right) \tag{10}$$

$$VRP_t^d = \frac{1}{T-t}\left(E_t^{\mathbb{P}}\left(\int_t^T \int_R x^2 v_s^{\mathbb{P}}(dx) ds\right) - E_t^{\mathbb{Q}}\left(\int_t^T \int_R x^2 v_s^{\mathbb{Q}}(dx) ds\right)\right) \tag{11}$$

For a particular threshold level k, the discrete portion of the variance risk premium is modified. This is done by simply changing the domain of the inner integral to account for only large moves.

$$VRP_t(k) = \frac{1}{T-t}\left(E_t^{\mathbb{P}}\left(\int_t^T \int_{|x|>k} x^2 v_s^{\mathbb{P}}(dx) ds\right) - E_t^{\mathbb{Q}}\left(\int_t^T \int_{|x|>k} x^2 v_s^{\mathbb{Q}}(dx) ds\right)\right) \tag{12}$$

Bollerslev and Todorov (2011) further decompose $VRP_t(k)$ into parts associated with negative jumps $VRP_t^+(k)$, and parts associated with positive jumps $VRP_t^-(k)$.

$$VRP_t^{+}(k) = \frac{1}{T-t}\left(E_t^{\mathbb{P}}\left(\int_t^T \int_{x>k} x^2 v_s^{\mathbb{P}}(dx)ds\right) - E_t^{\mathbb{Q}}\left(\int_t^T \int_{x>k} x^2 v_s^{\mathbb{Q}}(dx)ds\right)\right)$$

$$+ \frac{1}{T-t} E_t^{\mathbb{Q}}\left(\int_t^T \int_{x>k} x^2 v_s^{\mathbb{P}}(dx)ds - \int_t^T \int_{x>k} x^2 v_s^{\mathbb{Q}}(dx)ds\right) \tag{13}$$

Here k is the threshold that separates large jumps from small jumps. The first term on the right hand side of the equation reflects the compensation for time-varying jump intensity risk.

Based on the relationship between jump intensity and stochastic volatility (equation 7), the first term on the right hand side of the equation can be written as a function of diffusive volatility.

$$E_t^{\mathbb{P}}\left(\int_t^T \int_{x>k} x^2 v_s^{\mathbb{P}}(dx)ds\right) - E_t^{\mathbb{Q}}\left(\int_t^T \int_{x>k} x^2 v_s^{\mathbb{Q}}(dx)ds\right)$$

$$= \alpha_1^{+} \int_{x>k} x^2 v_s^{\mathbb{P}}(dx)ds \left(E_t^{\mathbb{P}}\left(\int_t^T \sigma_s^2 ds\right) - E_t^{\mathbb{Q}}\left(\int_t^T \sigma_s^2 ds\right)\right) \tag{14}$$

For Levy type jumps this part of the VRP should be zero. The second term reflects the difference between risk-neutral and objective jump intensities. But, this difference is evaluated under the $\mathbb{Q}$ measure.

$$FI_t(k) = VRP_t^{-}(k) - VRP_t^{+}(k) \tag{15}$$

The empirical methodology developed by Bollerslev and Todorov to estimate the fear uses high frequency intra-day data. They use 81 intra-day observations for 4751 trading days. I adopt a simpler methodology that only requires daily end-of-day observations of call and put prices.

4.4. Data and Methodology

I obtain daily option data from the OptionMetrics database. The database also contains daily closing bid and ask prices for American options, daily implied volatilities, and delta values. The option data spans the interval from January 1996 to December 2011. I consider only options with less than sixty days remaining to maturity.

I apply several filters to the option data to minimize measurement errors. Following Xing. et. al. (2010), I eliminate options that have a bid-ask average premium less than \$0.125. I remove options that have zero open interest and options with missing volume data to eliminate illiquid options. I remove options whose underlying stock price is less than \$5. I also exclude options with implied volatility lower than 3% or higher than 200% .

4.4.1. Estimating Risk Neutral Portion of Jump Risk from Local Steepness

I extract the risk neutral potion of the jump risk using equation (4) and (5). Combining the equations, the risk-neutral portion of jump risk is the following:

$$\left.\frac{\partial \sigma_i^{implied}(X,T)}{\partial X}\right|_{X=0} \approx L_i \lambda_i \mu_{ji} \approx s_i \approx IV_{i,t}^{PUT}(-.5) - IV_{i,t}^{CALL}(.5) \qquad (16)$$

or,

$$VS_{i,t}^{LOCAL} = IV_{i,t}^{PUT}(-.5) - IV_{i,t}^{CALL}(.5). \qquad (17)$$

The terms in parentheses are option deltas. To calculate the VS^{LOCAL} as defined in Yan (2011), for each underlying stock, I calculate the difference between the implied volatility of the put option and the implied volatility of the call option. I take the differences in implied volatilities between put options with $\Delta = -.5$ and call options with $\Delta = .5$. These options are very close to being at-the-money. Here VS^{LOCAL} is a proxy for down jump risk. After this calculation, I obtain one estimated value of VS^{LOCAL} per underlying security, per day.

Panel A of Table A.29 shows the measure of local skewness and summary statistics of implied volatilities across quintiles formed on local skewness. Panel A shows average implied volatilities across quintiles formed on VS^{LOCAL}. The average local steepness for the lowest quintile is -.041 and for the highest quintile is +.065.

4.4.2. Estimating Up Jump Risk from Right-hand Side Steepness

Lower value of implied volatility slope can be interpreted as relatively cheaper call options to put options (Cremers and Weinbaum 2008, Yan 2011). Similarly a higher implied volatility in OTM call options reflects buying pressure in OTM call options.

Out of the money call options can be used to isolate up jump risk. Particularly deep-out-of-the-money options remain worthless unless large movements occur before expiration. Intuitively, implied volatilities of deep OTM call options should go up when the market expects a positive jump. And implied volatilities of deep OTM call option should go down when the market expects no upward jumps. In other words the holder of a deep OTM call hopes that there will be an upward jump. Heuristically, it is possible to draw an analogy between $IV_{i,t}^{OTM\_CALL}$ and hope. Higher IV in OTM calls represent hope, while a lower IV in OTM calls represent a lack of hope (or fear). Similar to Xing et. Al (2010) measure, I construct a measure for the slope of the right side of the implied volatility smile.

$$VS_{i,t}^{RIGHT} = IV_{i,t}^{OTM\_CALL} - IV_{i,t}^{ATM_{CALL}} \tag{18}$$

I use $VS_{i,t}^{RIGHT}$ as a proxy for the up jump measure.

Following the logic in equation (12), call options that are sufficiently OTM represent up jump risk. An increase in implied volatility of OTM call options, relative to the implied volatility of ATM call options, indicates that the option market perceives an upward jump to be likely. Therefore, up jump risk can be characterized as the difference between IV^{OTM_CALL} and IV^{ATM_CALL}. I calculate VS^{RIGHT} , the measure of steepness of the right hand side of the volatility smile , by using equation (18). To calculate the VS^{RIGHT} I define options as ATM where $0.98 < \frac{K}{S} < 1.02$ and as OTM where $1.08 < \frac{K}{S} < 1.12$. For each underlying security I calculate the average implied volatility of all OTM call options and average implied volatility of all ATM call options. For each underlying security I calculate the difference between the average implied volatility of OTM call options and average implied volatility of ATM call options.

Panel B of Table A.29 shows average implied volatilities across quintiles formed on VS^{RIGHT}. The average steepness for the lowest quintile is -.048 and the average steepness for the highest quintile is .160. In contrast to local steepness (VS^{LOCAL}), the right side steepness (VS^{RIGHT})

has a wider range. The wider tails of the right side steepness measure capture the increasing "fear premium" associated with a jump process.

4.4.3. Estimating the Implied Fear Premium

Following the Bollerslev and Todorov (2011) approach, I construct an implied volatility (IV) based measure to capture fear by taking the difference between a measure for down jump and a measure for up jump.

Estimation of Fear premium requires both VS^{LOCAL} and VS^{RIGHT}. According to the definition of fear index in equation (15), fear can be characterized as the difference between a down jump probability and up jump probability. Based on this relationship I construct the final measure of fear is constructed as the following:

$$Fear = Prob^{\mathbb{Q}}(down\ jump) - Prob^{\mathbb{P}}(up\ jump) = VS_{i,t}^{LOCAL} - VS_{i,t}^{RIGHT}. \qquad (19)$$

The estimation of fear index directly using equation (19) creates a noisy measure, due to temporal variation of the implied volatilities. To get a smoother estimate, I adopt a rolling regression approach to extract the difference between VS^{LOCAL} and VS^{RIGHT}.

To extract the fear premium, I utilize the following regression:

$$VS_i^{RIGHT} = \alpha_i + \beta_i(VS_i^{LOCAL}) + \varepsilon_i \qquad (20)$$

where VS_i^{RIGHT} is the right side steepness for firm i, VS_i^{LOCAL} is the local steepness, α_i is the intercept, β_i is the parameter associated with VS_i^{LOCAL}. I use estimates of α_i as the proxy for fear premium.

I run regression (20) each day, for each security using observations from the last 60 days. I use rolling regressions to ensure that I have a unique value for the fear premium for each security, each day.

Table A.30 shows the right side steepness measures as well as the risk neutral portion of jump risk over quintiles formed on fear premium. Column (1) reports the average fear premium. Column (2) reports the local measure of steepness. The local measure of steepness falls from quintile 1 to quintile 3 and then rises to quintile 5. Column (3) reports the right side steepness of volatility smile. Average value of VS^{RIGHT} is monotonically increasing in fear premium. This is evidence that the fear premium is a part of VS^{RIGHT}, and not a part of VS^{LOCAL}.

4.5. Evidence of Fear from S&P 500 Options

4.5.1. The Fear Index

I define the Fear Index as the calculated fear premium from S&P 500 index options. For each date, Fear is estimated using equation (20) on all options that have 5 to 180 days to maturity. Values of α from the regression represent the measure of fear.[7] Following this strategy I get an estimate of fear for the entire time series. Figure B.9 presents the estimated fear premium from March 1996 to December 2011.

The dark solid line presents the IV based fear index. The lighter solid line is the fear index estimated by Bollerslev and Todorov (2011). I overlaid the two measures to make comparison easier. My measure of fear, which is derived from daily closing implied volatilities, resembles the Bollerslev-Todorov (2011) measure for fear very closely.

Spikes in Fear can be seen around major market moving incidents. The spike in fear in late 1998 coincides with the LTCM incident. The largest spike in fear is observed in October of 2008 around the height of the financial crisis and collapse of Lehman Brothers. Interestingly, I also see a mid-sized spike around the summer of 2010 when many market participants feared a double-dip recession. Although, there was no real market crash, my measure of fear seems to capture the panic around that time. The Bollerslev-Todorov (2011) measure is always negative, while the IV based measure is positive in periods around 2005 and 2006. It is possible to loosely interpret these as periods of excessive optimism. This is also the time when sub-prime mortgages were creating the real-estate bubble, so it is not too far-fetched to argue that this is something akin to irrational exuberance.

[7] an alternative version of fear index is shown in Figure B.12

4.5.2. Evidence of Fear from Short Put Option Positions

The next question to answer is that whether the fear index is truly a measure of fear. If the IV based measure truly represents fear, the market should not move down significantly following a spike in fear. Periods of high fear should also coincide with irrationally high demand for out of the money put options as investors seek protection against a crash. If high fear periods are not followed by significant downward market moves, these put options purchased at irrationally high prices will expire out of the money.

The logic described above gives me the opportunity to carry out a natural experiment to test whether the IV based fear measure truly captures panic. I take the following steps to carry out the experiment:

For each month in the sample I rank the days based on fear. Days when fear is the highest, are assigned a rank of 5. Days when fear is the lowest are assigned a rank of 1. Next, on any day with the highest fear, I short put options with strikes 10% below the spot price.[8] In particular, I short all options with maturity between 30 and 90 days. Once the options are sold, I stay short till the expiry of the options. Simultaneously, on days with the lowest fear, I purchase put options that are approximately 10% OTM and hold them till expiry. I purchase all options that fit the moneyness criteria and have between 30 to 90 days till expiry. In other words, I sell put options during high fear periods and purchase put options during low fear (or relative confidence) periods.

Table A.31 shows the results from following this strategy. Panel A shows returns on short put options for the 5 levels of fear, ignoring transaction costs. Options sold during the lowest fear periods earn a return of 32.23%. Options sold during the highest fear periods earn a return of 73.36%. The short put option profits increase monotonically with the degree of fear. This result suggests that fear is correlated with the irrational expectation of a down jump. In fact, the results imply that a put option shorted during the lowest fear period has the highest probability of expiring

[8] the options are approximately 10% out-of-the-money. If an option exactly 10% OTM is not found, I short the put option where $\frac{K}{S}$ is closest to .90

in the money. A put option shorted during the highest fear period has the lowest probability of expiring in the money. The strategy that implements shorting puts during high fear and purchasing puts during low fear periods earns a return of 60.63% and is statistically significant.

Panel B of table A.31 shows the returns on short put options for the same strategy, accounting for transactions costs. Options shorted during the lowest fear period earn a return of 13.19% while options shorted during highest fear periods earn a return of 73.33% after considering all transactions cost. A hedge portfolio that implements shorting puts during high fear and purchasing puts during low fear earns 45.50%.

If estimation of downside risk was correct, I would not expect to see this pattern. The completely monotonic pattern of increasing return on short put option quintiles indicates that the IV based measure captures irrational overreaction to downside risk.

To further test the validity of my measure, I conduct the same test with put options 5% out of the money. Panel A of table A.32 ignores any transactions costs. The lowest fear quintile earns a return of 36.25%. The short option selling return increases to 74.54% for the highest fear quintile. A hedging strategy earns 48.59%.

Panel B of table A.32 considers transaction costs. Short put option positions initiated during the lowest fear periods earn 23.00%. Short put options positions initiated during the highest fear periods earn 71.16%. The transactions costs reduce the returns on all quintiles. The hedging strategy earns profits of 38.64%. The results in panels A and B imply that the options sold during the high fear periods are much less likely to expire in the money than the options shorted during low fear periods. Even in the case of options that are only 5% out of the money, the downward move is the least likely to be realized for options shorted during periods of high fear.

4.5.3. Evidence of Fear from Short Put Option Return Time Series

To visualize option returns during crisis periods, I map out the returns on fear quintiles from 1996 to 2011.

Figure B.10 shows the short OTM put option returns for the highest and lowest fear quintiles. The solid blue line represents the returns on short put options during low fear periods. The dashed red line represents the returns on short put positions during high fear periods.

I see that for the most part of the time series, short put option on S&P 500, with 30 to 90 days to maturity and 10% OTM strikes, expire OTM. In this case the short seller collects the entire premium of the put option. I consider this a 100% return. In figure B.9, the top line has a height of 1 along the y-axis. This represents the 100% return. Around periods of major market movements, short put options experience very large losses. The largest downward spike observed in 2008 has a value of -60 along the y-axis. That represents a loss of 6,000% relative to the shorted value of the option premium.

The most important observation from figure B.9 is that the solid blue line, which represents options sold during lowest levels of fear, suffers the worst losses. The options sold during highest fear levels, suffers a loss that is relatively much smaller. This again lends support to the notion that the IV based measure captures crash-o-phobia.

Figure B.11 shows a closer picture of all fear quintiles during the 2008 crisis. Quintile 1 is the lowest fear and quintile 5 is associated with highest fear. The solid blue line associated with the lowest fear levels, suffer the worst losses. The losses decrease for each higher degree of fear. The highest fear quintile, takes the lowest loss.

4.5.4. Fear and Tail Risk

I calculate a rolling value-at-risk measure to define tail risk. Based on the historical volatility of S&P 500 returns, I calculate the threshold that defines an 1% tail event. For each date in the sample, I calculate a 60 day moving average of volatility. For simplicity I adopt a normal distribution to calculate VaR. The rolling estimate of volatility is used as the standard deviation parameter in the normal distribution. Next, the move corresponding to a 99% tail event is calculated. Following this procedure, I calculate the 1-day VaR measure. The VaR measure is then multiplied by square root of 30, 60 and 90 to calculate 30, 60 and 90 day VaR. I specifically pick these intervals because the short OTM put options discussed so far have anywhere between 30 to 90 days to maturity.

Table A.33 shows the frequency of tail violations over 30, 60 and 90 days across the fear quintiles. Tails are violated only for the 2 quintiles with the lowest fear. Tail events are not observed following high fear quintiles. Rather, the periods of lowest fears are followed by large down moves. This is consistent with the claim that the measure of fear captures the irrational component from the implied volatility smile.

4.6. Equity Option Portfolio Returns

I construct portfolios of options based on daily observed values of fear premium. I sort options into quintiles based on the value of fear premium of the underlying security. Quintile 1 consists of options written on stocks with the lowest fear score and quintile 5 consists of options written on stocks with highest fear score. Each option in the portfolio is held till maturity.

Table A.34 reports the time series average of all holding period returns for selling put options over the entire sample. The average option holding period over all formation period is 35 days. Panel A presents returns for selling OTM put options. I find that the option returns increase monotonically from quintile 1 to quintile 5. Quintile 5 earns highest returns of 5.61% and quintile 1 earns the lowest returns of 0.73%. The returns on all portfolios are highly statistically significant. I also calculate the returns on a zero-investment hedge portfolio that assumes a long position in options in quintile 1 and short position in options in quintile 5. The time series average of all holding periods for this hedge portfolio is 5.61% and is statistically significant.

Panel B of table A.34 presents the returns for selling ATM put options over quintiles formed on fear premium. Option selling returns generally increase over the quintiles of fear. The zero cost hedge portfolio for ATM put options earns an average holding period return of 4.45% and is statistically significant.

Panel C of table A.34 shows the returns for selling ITM put options over quintiles formed on fear score. Interestingly enough, I do not see any clear pattern of option selling returns over the quintiles. The results indicate that fear does not affect ITM options the way it affects OTM or even ATM options. When investors fear a crash, they seek protection by purchasing puts that have a lower strike price than the current spot price. An OTM put option, without any intrinsic value has a lower premium ($ price of the option) than an ITM option that has higher premium. To the market participants, OTM options serve the purpose of insurance, rather than ITM options. It is unlikely that market participants buy ITM options for protection against a jump type move.

To summarize, the stocks for which the fear premium is highest, the holders of those stocks will pay irrationally high prices to purchase protection. The natural avenue to do this would be to purchase put options. The strategy takes advantage of this phenomenon by selling overpriced put options. Table A.33 shows that the zero cost hedge portfolios earn positive and significant returns regardless of the moneyness of the option.

I also construct portfolios for call options. Table A.35 reports returns on short call option portfolios formed on the fear premium. Panel A of table A.35 presents returns on OTM call options written over the quintiles of fear premium. Like OTM put options, returns on OTM call options increase with fear premium. The zero cost hedge portfolio earns a return of 11.33%. The results indicate that stocks subject to high levels of fear of crash do not usually experience positive jumps. The OTM call options sold do not finish in the money and the selling strategy earns the premium. This finding lines up with the definition of fear well. Fear is associated with a negative jump. When a lot of market participants are weary of a negative jump, it is unlikely that a positive jump will occur. This finding indicates that selling short straddles may be very profitable during periods of high fear.

Panel B of table A.35 shows that the average return on call options sold decrease with fear premium. Returns decrease from positive 3.27% to negative 6.30% from quintile 1 to quintile 5. These results coincide with the notion that despite the irrational fear of a crash, the crash does not occur in reality and stocks subject to highest crash fear increase in price. In this scenario, the call option writer to incurs a loss.

Panel C of table A.35 exhibits the same pattern as panel B. Portfolio returns monotonically decrease from quintile 1 to quintile 5. The zero cost hedge portfolio earns a negative return of 4.80%. This finding indicates that it is bad strategy to sell call options on stocks with high fear premium. Overall, the results in table A.34 indicate that it is unwise to write ATM or ITM call options on stocks that are inexpensive due to irrational fear.

It is important to note that put and call options serve two very different purposes for high fear quintiles. Put options function as protection against potential crashes. Call options serve as a vehicle for contrarian investors who realize that stocks are irrationally oversold. Therefore, it is no surprise to see that in general put options on high fear quintiles earn lower returns and call options earn higher returns. As a result, a put option writing strategy is profitable while a call option writing strategy is not always profitable.

4.7. Option Portfolio Returns in the Presence of Market Frictions

Previous literature documents that transactions cost in the option market have a significant impact on profitability of option portfolio returns. To make sure that the strategies are robust to these market frictions, I discuss the impact of transactions costs in this section.

My analysis thus far has been conducted using the mid-point price of quoted bid and ask prices. To calculate the returns to option portfolios in the presence of transactions costs, I consider the bid and ask prices for the portfolio strategy. De Fontnouvelle, Fisher, and Harris (2003) and Mayhew (2002) show that the effective spread is less than half of the quoted spread. I use 100% of the quoted spread to measure the returns on the portfolios to examine the worst case scenario. The portfolio strategy assumes a short position in an option and holds that position till maturity. So, the strategy is subject to transactions costs only at the initiation of the position.

Table A.36 presents the returns on selling put option portfolios, in the presence of transactions costs over quintiles formed on fear premium. I calculate selling returns by considering the quoted bid price as the initial cash inflow. Once sold, the options are held till maturity. I calculate the value of the option on the expiry date, and use the difference of maturity date value and initial profit to calculate the option returns in the presence of transactions costs.

Panel A of table A.36 shows returns on selling OTM put option portfolios controlling for the bid-ask spread. The profitability of each of the option portfolios are significantly lower compared to panel A of table A.34. The returns on quintile 1 of table A.34 is .73% and quintile 5 is 6.34%. In contrast, the return on quintile 1 of table A.36 is negative 1.94% and return on quintile 5 is 2.69%. Although the returns are smaller here for all five quintiles, the average return on the zero cost hedge portfolio is 4.63%. This return is only slightly lower than the strategy without transactions cost.

Panel B shows returns from selling ATM put options. The returns on these option portfolios have high standard deviations and are not statistically significant after accounting for transaction costs. Panel C presents returns from selling ITM put options. Although the average returns for selling ITM put options are significant for each decile, I do not see any patterns over the quintiles. Unlike table A.33, the hedge portfolio earns a negative return of 37.80%. The results on the ATM and ITM options do not have the high leverage associated with OTM options. The ITM put options do not function as insurance against negative jump risk. Therefore, selling ITM put options often finish in the money. The fear measures the irrational fear of a large downside move. When the strategy sells ITM put options, the stock might move down enough so that the ITM put options finish in the money but not enough so that the OTM put options finish in the money. The results indicate that after controlling for market frictions selling OTM put option is still profitable. However, I find that profitability of the strategy diminishes for ITM options after controlling for the bid-ask spread.

In table A.37, I present the returns on selling call option portfolios. Panel A shows that in the presence of market frictions, all five quintiles of written OTM call options earn negative returns. The options written on stocks with highest fear earn the lowest returns. This is contrary to the finding in table A.35, where I did not consider transactions costs. The options with higher fear premium earn lower returns after controlling for transactions cost.

Panel B and panel C present results for selling ATM and OTM call options. In both cases, the zero investment hedge portfolio earns negative returns. One possibility is that options written on stocks with high levels of crash fear often bounce back, causing the options sold to expire in the money. My measure of fear premium captures the irrational portion of jump risk. When the market corrects itself from the irrational fear, the stocks move up. Consequently, the options written on the high fear quintiles finish in the money and the option writer incurs a loss.

Between, table A.35 and table A.37, five out of six times losses from selling call options are greater when fear is higher. The correct way to take advantage of high fear would be to take contrarian positions (i.e. long call options on high fear quintiles). Results indicate, shorting calls for high fear stocks is not good for the investors' wealth.

4.8. Conclusion

Financial asset prices can deviate from their fundamental values as long as some investors are irrational. The results of this study demonstrate that, the fear of a negative jump is associated with purchases of protection against a negative jump at irrationally high prices. In this study I develop a measure to capture the irrational component of negative jump risk.

The main results lend support to the hypothesis that investors' fear of a crash causes them to buy insurance at irrationally high prices. By comparing returns on short put option portfolios, this study empirically tests whether the irrationality gets priced into options. The degree of irrationality is correlated with the fear premium. The results are consistent with cognitive biases documented in the literature. Prospect Theory (Kahneman and Tversky, 1979, 1983) argues that people overpay for claims when the probability of an event occurring is small but potential payoff is large (i.e. lottery tickets). Consistent with prospect theory, I find that fear premiums are highest for OTM options. The mispricing due to over-estimation of risk is arbitrage-able and can be used to devise profitable trading strategies.

CHAPTER 5

OVERALL CONCLUSIONS

This dissertation addresses the information that is embedded into option prices. Whenever traders have insider information it is likely to be reflected in the option prices first. This dissertation investigates multiple issues that address the gap in information content between the equity and option markets. First, I find that the information sets in the option and equity markets are different. I construct a metric based on divergence from put call parity. The divergence metric captures information that is present in the option market, but not yet revealed in the equity market. This metric predicts the future direction of the underlying security reliably. Divergence is also predictive of extreme tail events. The existence of predictability suggests that the information sets in the two markets differ from each other. I find evidence that the option market leads the equity market. The leading nature of the option market information set is consistent with the insider information hypothesis rather than the irrational overreaction hypothesis.

Second, I analyze the difference between the equity and option market participants. I construct option and equity market signals. The option market signals are of higher quality than equity market signals. When I form bi-variate strategies, equity market signals predict the direction of the security only when they are consistent with option market signals. This finding reveals that equity market participants make excess returns as long as they follow the option market signals. The irrational participants in the equity market, who do not follow the option market signals, do not make positive returns.

Finally, this dissertation explores irrationality within the option market. I find that out of the money put options are overvalued when market participants fear a crash. I construct a measure of fear from the daily observed implied volatilities in the market. Tests reveal that the fear premium can be used to construct profitable option selling strategies, when irrational excess demands for put options exist. I find that an extreme tail event is more likely to occur after a period of low fear, rather than high fear. This finding confirms the irrational nature of fear. This section of the dissertation consolidates multiple strands of literature dealing with implied jump risk, slope of the volatility smile and variance risk premium embedded into options.

Additional research could extend this study by extracting the information embedded in the convexity of the implied volatility smile. Using the implied volatilities from the continuum of option strikes it is possible to construct the implied risk-neutral density function. The risk-neutral density function may reveal further information about the underlying asset that is otherwise unobservable.

APPENDIX A

TABLES

Table A.1

Divergence and Future Stock Performance (1-day Holding Period)

Over the sample period of 2004 to 2009, at the end of each trading day, I sort stocks into 10 groups by their most recently calculated value of divergence from put-call parity and assign them to decile portfolios. Once the portfolios are formed, each stock is held for 1 trading day. I then compute the equally-weighted returns over the next day. The returns presented in the table are average returns over all formation periods. Decile 1 represents a portfolio consisting of firms with the lowest divergence and decile 10 represents a portfolio consisting of firms with the highest divergence. The (10 -1) portfolio reports the average returns of a zero investment hedge portfolio that is long the lowest divergence portfolio and short the highest divergence portfolio.

Divergence Portfolio	Mean Divergence	Daily Average Returns	t-stat
1	-2.0066	0.2156%	4.41
2	-0.3890	0.1268%	2.83
3	-0.1598	0.1007%	2.32
4	-0.0229	0.0693%	1.62
5	0.0865	0.0513%	1.19
6	0.1922	0.0232%	0.54
7	0.3147	-0.0015%	-0.03
8	0.4864	-0.0284%	-0.61
9	0.8105	-0.0740%	-1.49
10	2.7698	-0.1574%	-2.85
10-1		0.3730%	18.86

Table A.2

Divergence and Future Stock Performance (3-day Holding Period)

Over the sample period of 2004 to 2009, at the end of each trading day, I sort stocks into 10 groups by their most recently calculated value of divergence from put-call parity and assign them to decile portfolios. Once the portfolios are formed, each stock is held for 3 trading days. I then compute the equally-weighted returns over the 3 day holding period. The returns presented in the table are average returns over all formation periods. Decile 1 represents a portfolio consisting of firms with the lowest divergence and decile 10 represents a portfolio consisting of firms with the highest divergence. The (10 -1) portfolio reports the average returns of a zero investment hedge portfolio that is long the lowest divergence portfolio and short the highest divergence portfolio.

Cumulative return over 3 day holding period

Divergence Portfolio	Mean Divergence	Daily Average Returns	t-stat
1	-2.0066	0.3023%	4.4167
2	-0.3890	0.1719%	2.7584
3	-0.1598	0.1341%	2.2136
4	-0.0229	0.1068%	1.8163
5	0.0865	0.0812%	1.3720
6	0.1922	0.0569%	0.9427
7	0.3147	0.0311%	0.5009
8	0.4864	-0.0086%	-0.1319
9	0.8105	-0.0701%	-1.0143
10	2.7698	-0.1843%	-2.3325
10-1		0.4866%	18.2940

Table A.3
Divergence and Future Stock Performance

Over the sample period of 2004 to 2009, at the end of each trading day, I sort stocks into 10 groups by their most recently calculated value of divergence from put-call parity and assign them to decile portfolios. Once the portfolios are formed, I construct a zero investment hedge portfolio that is long the lowest divergence portfolio and short the highest divergence portfolio. The hedge portfolio is held for 1, 3, 6, 9, 12, 15 and 18 days. Next, for each formation period, holding period cumulative returns are calculated for 1, 3, 6, 9, 12, 15 and 18 days. The returns presented in the table are average of the cumulative returns for over all formation periods.

Hedge Portfolio Return over Multiple Holding Periods		
Holding Period (in days)	Cumulative Returns	t-stat
1	0.3730%	18.87
3	0.4866%	18.29
6	0.5628%	17.20
9	0.7430%	16.95
12	0.8996%	17.69
15	1.0647%	18.29
18	1.2002%	18.48

Table A.4

Divergence and Future Stock Performance over Multiple Holding Periods

Over the sample period of 2004 to 2009, at the end of each trading day, I sort stocks into 10 groups by their most recently calculated value of divergence from put-call parity and assign them to decile portfolios. Each of these 10 portfolios are held for 1, 3, 6, 9, 12, 15, 18 days. Next, the cumulative holding period return is calculated for each formation period. The returns presented in this table are the average of the cumulative holding period returns. The (10 -1) portfolio reports the average cumulative holding period returns of a zero investment hedge portfolio that is long the lowest divergence portfolio and short the highest divergence portfolio.

Divergence Portfolio	Mean Divergence	1 Day	3 day	6 day	9 day	12 day	15 day	18 day
1	-2.01	0.22%	0.30%	0.39%	0.56%	0.68%	0.78%	0.94%
2	-0.39	0.13%	0.17%	0.22%	0.32%	0.40%	0.47%	0.56%
3	-0.16	0.10%	0.13%	0.18%	0.29%	0.34%	0.40%	0.48%
4	-0.02	0.07%	0.11%	0.16%	0.25%	0.30%	0.35%	0.43%
5	0.09	0.05%	0.08%	0.12%	0.21%	0.25%	0.31%	0.38%
6	0.19	0.02%	0.06%	0.09%	0.17%	0.22%	0.26%	0.33%
7	0.31	0.00%	0.03%	0.07%	0.17%	0.20%	0.25%	0.31%
8	0.49	-0.03%	-0.01%	0.03%	0.11%	0.15%	0.17%	0.24%
9	0.81	-0.07%	-0.07%	-0.05%	0.02%	0.02%	0.01%	0.08%
10	2.77	-0.16%	-0.18%	-0.17%	-0.19%	-0.22%	-0.29%	-0.26%
1-10		0.37%	0.49%	0.56%	0.74%	0.90%	1.06%	1.20%

Table A.5
Divergence and Empirical Probability of a 99% Tail Violation
(based on a fitted t-distribution)

Over the sample period of 2004 to 2009, for each security, the returns are fitted to a t-distribution. To fit the t-distribution, maximum likelihood-estimation is used to find the optimal degree of freedom parameter. After that, the percentage Value-at-Risk (VaR) is calculated at the 99% confidence level. The multiple day VaR measure is created by scaling the 1-day VaR by $\sqrt{t}$, where t represents the holding period. The number of tail violations is calculated by counting occurrences of return on the security larger than the 99% VaR. For each divergence portfolio, the empirical probability of a tail violation is calculated as the number of tail violations divided by the total number of return observations. The table presents these probabilities for 1, 3, 6, 9, 12, 15 and 18 day holding periods.

Divergence Portfolio	Mean Divergence	1 Day	3 day	6 day	9 day	12 day	15 day	18 day
1	-2.01	0.83%	0.43%	0.25%	0.34%	0.29%	0.31%	0.30%
2	-0.39	0.81%	0.41%	0.23%	0.30%	0.27%	0.27%	0.28%
3	-0.16	0.79%	0.39%	0.20%	0.27%	0.24%	0.27%	0.26%
4	-0.02	0.77%	0.37%	0.20%	0.27%	0.23%	0.24%	0.26%
5	0.09	0.75%	0.37%	0.20%	0.28%	0.25%	0.26%	0.26%
6	0.19	0.80%	0.39%	0.20%	0.29%	0.25%	0.27%	0.27%
7	0.31	0.85%	0.41%	0.22%	0.29%	0.26%	0.28%	0.28%
8	0.49	0.94%	0.47%	0.27%	0.36%	0.30%	0.32%	0.31%
9	0.81	1.08%	0.58%	0.34%	0.44%	0.38%	0.41%	0.41%
10	2.77	1.36%	0.81%	0.55%	0.70%	0.64%	0.66%	0.66%

Table A.6
Divergence and Empirical Probability of a 99% Tail Violation
(based on a fitted normal distribution)

Over the sample period of 2004 to 2009, for each security, the returns are fitted to a normal distribution. To fit the normal distribution, mean and variance of each security is calculated. After that, the percentage Value-at-Risk (VaR) is calculated at the 99% confidence level. The multiple day VaR measure is created by scaling the 1-day VaR by $\sqrt{t}$, where t represents the holding period. The number of tail violations is calculated by counting occurrences of return on the security larger than the 99% VaR. For each divergence portfolio, the empirical probability of a tail violation is calculated as the number of tail violations divided by the total number of return observations. The table presents these probabilities for 1, 3, 6, 9, 12, 15 and 18 day holding periods.

Divergence Portfolio	Mean Divergence	1 Day	3 day	6 day	9 day	12 day	15 day	18 day
1	-2.01	1.45%	0.82%	0.51%	0.65%	0.59%	0.62%	0.63%
2	-0.39	1.37%	0.75%	0.46%	0.59%	0.54%	0.58%	0.57%
3	-0.16	1.32%	0.71%	0.43%	0.57%	0.50%	0.55%	0.56%
4	-0.02	1.29%	0.70%	0.42%	0.55%	0.48%	0.52%	0.54%
5	0.09	1.27%	0.70%	0.41%	0.56%	0.50%	0.55%	0.56%
6	0.19	1.33%	0.72%	0.42%	0.58%	0.51%	0.56%	0.58%
7	0.31	1.41%	0.75%	0.44%	0.59%	0.53%	0.57%	0.59%
8	0.49	1.56%	0.86%	0.54%	0.69%	0.60%	0.65%	0.67%
9	0.81	1.75%	1.03%	0.64%	0.82%	0.76%	0.82%	0.81%
10	2.77	2.15%	1.38%	0.95%	1.20%	1.13%	1.20%	1.17%

Table A.7
Fama French Three Factor Regression

The table presents results of time-series regression of returns on Fama-French three factors. The three factor regressions are ran by regressing returns on market excess return (RM–Rf), small market capitalization minus big (SMB), and high book-to-market ratio minus low (HML) factors. Over the period of April 2009 to October 2009, regression (1) presents the parameters estimates for the entire sample. Regressions (2) and (3) present the parameters estimates for the subsample of observations where divergence is negative, and where divergence is positive, respectively.

VARIABLES	(1) Return	(2) Return (Divergence<0)	(3) Return (Divergence>0)
β_{Mkt}	0.984***	1.015***	0.790***
	(0.0153)	(0.0178)	(0.0280)
β_{SMB}	0.572***	0.526***	0.559***
	(0.0275)	(0.0312)	(0.0534)
β_{HML}	0.0543**	-0.00768	0.123***
	(0.0254)	(0.0294)	(0.0469)
α	0.00252***	**0.00629*** **	**-0.00810*** **
	(0.000178)	**(0.000203)**	**(0.000354)**
R-squared	0.286	0.291	0.224

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.8
Fama-French-Carhart Four Factor Regression

The table presents results of time-series regression of returns on Fama-French-Carhart four factors. The three factor regressions are ran by regressing returns on market excess return (RM–Rf), small market capitalization minus big (SMB), and high book-to-market ratio minus low (HML), and up momentum minus down (UMD) factors. Over the period of April 2009 to October 2009, regression (1) presents the parameters estimates for the entire sample. Regressions (2) and (3) present the parameters estimates for the subsample of observations where divergence is negative, and where divergence is positive, respectively.

VARIABLES	(1) Return	(2) Return (Divergence<0)	(3) Return (Divergence>0)
β_{Mkt}	0.912***	0.901***	0.753***
	(0.0186)	(0.0214)	(0.0349)
β_{SMB}	0.602***	0.578***	0.572***
	(0.0279)	(0.0316)	(0.0540)
β_{HML}	-0.0123	-0.125***	0.0952*
	(0.0272)	(0.0318)	(0.0495)
β_{UMD}	-0.104***	-0.173***	-0.0501*
	(0.0155)	(0.0180)	(0.0284)
α	0.00224***	**0.00587*** **	**-0.00828*** **
	(0.000183)	**(0.000207)**	**(0.000368)**
R-squared	0.287	0.294	0.224

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.9
Various Measures of Divergence

This table reports mean and standard deviations of the divergence metric calculated based on options from different strike prices and times to maturity. Panel A shows the summary statistics of divergence when divergence is derived only from at the money options $\left(-.1 < \ln\left(\frac{K}{S}\right) < .1\right)$, panel B shows results when divergence is derived from in the money options $\left(-.3 < \ln\left(\frac{K}{S}\right) < -.1\right)$ and panel C shows results when divergence is derived from out of the money options $\left(.1 < \ln\left(\frac{K}{S}\right) < .3\right)$. I classify options with 5 to 30 days to maturity as very short term, options with 31 to 90 days to maturity as short term, options with 91 to 182 days to maturity as mid-term, and options with 183 to 365 days to maturity as long term.

Panel A: At The Money Options

	Very Short Term	**Short Term**	**Mid Term**	**Long Term**
Mean divergence	0.001	0.068	0.231	0.351
Standard deviation of divergence	0.148	0.224	0.441	0.612

Panel B: In The Money Options

	Very Short Term	**Short Term**	**Mid Term**	**Long Term**
Mean divergence	0.008	0.068	0.152	0.251
Standard deviation of divergence	0.179	0.215	0.349	0.445

Panel C: Out of The Money Options

	Very Short Term	**Short Term**	**Mid Term**	**Long Term**
Mean divergence	0.028	0.097	0.209	0.302
Standard deviation of divergence	0.199	0.275	0.405	0.498

Table A.10

Various Measures of Divergence and Returns

This table reports average daily returns on portfolios formed on various measures of divergence. Reported returns are based on a 1-day holding period after formation. The divergence metric is calculated based on options from different strike prices and times to maturity. Over the period of April 2009 to October 2009, Panel A shows the daily average returns of portfolios formed on divergence when divergence is derived only from at the money options $\left(-.1 < \ln\left(\frac{K}{S}\right) < .1\right)$, panel B shows results when divergence is derived from in the money options $\left(-.3 < \ln\left(\frac{K}{S}\right) < -.1\right)$ and panel C shows results when divergence is derived from out of the money options $\left(.1 < \ln\left(\frac{K}{S}\right) < .3\right)$. I classify options with 5 to 30 days to maturity as very short term, options with 31 to 90 days to maturity as short term, options with 91 to 182 days to maturity as mid-term, and options with 183 to 365 days to maturity as long term.

Panel A: Divergence measured from At-the-money options

	Very short term		Short Term		Mid-Term		Long-Term	
	Average Return	t-value	Average Return	t-value	Average Return	t-value	Average Return	t-value
1	0.001652	7.017939	0.001300	5.834225	0.001138	5.335400	0.001024	4.954630
2	0.001428	6.071657	0.001058	4.615624	0.001143	5.122766	0.000994	4.472325
3	0.001190	5.104006	0.001080	4.719445	0.001028	4.513152	0.000953	4.187936
4	0.000989	4.246392	0.000888	3.905512	0.000867	3.754249	0.000851	3.667951
5	0.000814	3.478371	0.000656	2.819282	0.000878	3.771838	0.000818	3.487910
6	0.000673	2.882388	0.000594	2.524082	0.000755	3.246856	0.000787	3.335120
7	0.000646	2.737693	0.000458	1.944615	0.000551	2.327805	0.000633	2.607372
8	0.000481	2.017984	0.000342	1.442958	0.000454	1.874999	0.000519	2.129508
9	0.000303	1.249777	0.000173	0.714151	0.000322	1.297005	0.000349	1.415882
10	-0.000191	-0.755223	-0.000218	-0.879321	-0.000059	-0.234633	-0.000020	-0.078217

Panel B: Divergence measured from In-the-money options

	Very short term		Short Term		Mid-Term		Long-Term	
	Averag e Return	t-value	Average Return	t-value	Average Return	t-value	Average Return	t-value
1	0.001547	6.688901	0.001810	9.688996	0.002111	11.483400	0.002843	15.838267
2	0.001904	7.955622	0.002034	9.857525	0.002240	11.277905	0.002862	14.628227
3	0.001962	8.124321	0.002192	10.523702	0.002216	10.773197	0.002817	13.877784
4	0.001676	7.081073	0.002074	9.813078	0.002163	10.294758	0.002884	14.124889
5	0.001728	7.472577	0.001941	9.242102	0.002101	9.891295	0.002764	12.984706
6	0.001418	5.945088	0.001977	9.302907	0.001966	9.181004	0.002722	12.716849
7	0.001335	5.601038	0.001673	7.738773	0.001807	8.282717	0.002677	12.352849
8	0.001098	4.645335	0.001445	6.718381	0.001708	7.689630	0.002845	12.779211
9	0.000979	3.980277	0.001266	5.700173	0.001660	7.213470	0.002707	11.940244

Table A.10 - continued

10	0.000894	3.328226	0.001221	5.193388	0.001425	5.905643	0.002632	11.195746
Panel C: Divergence measured from Out-the-money options								
	Very short term		Short Term		Mid-Term		Long-Term	
	Average Return	t-value	Average Return	t-value	Average Return	t-value	Average Return	t-value
1	0.000231	0.87028	0.000324	1.488476	0.000152	0.727935	-0.00041	-2.07021
2	0.000474	1.875463	0.000332	1.485942	0.000131	0.584037	-0.00063	-2.93128
3	0.000191	0.757186	6.40E-05	0.281118	4.69E-07	0.002004	-0.00079	-3.45963
4	4.55E-05	0.183341	-0.00012	-0.52332	-0.00024	-0.98461	-0.001	-4.19454
5	0.000168	0.659466	-0.00051	-2.15993	-0.00041	-1.67124	-0.00123	-5.11639
6	-0.00011	-0.4466	-0.00072	-3.02618	-0.00068	-2.78834	-0.00141	-5.81884
7	-0.00021	-0.8345	-0.00088	-3.70786	-0.00104	-4.24668	-0.0017	-6.96814
8	-0.00048	-1.82586	-0.00107	-4.48948	-0.00124	-5.02144	-0.00184	-7.46681
9	-0.00073	-2.7867	-0.00145	-6.10494	-0.00161	-6.40294	-0.00235	-9.34091
10	-0.00168	-6.0171	-0.00223	-9.01126	-0.00234	-9.00512	-0.00315	-12.1183

Table A.11
Various Measures of Divergence and Hedge Portfolio Returns

This table reports average daily returns on zero investment hedge portfolios that are long the lowest divergence portfolio and short the highest divergence portfolio. These hedge portfolios are constructed with various measures of divergence. Reported returns are based on a 1-day holding period after formation. The divergence metric is calculated based on options from different strike prices and times to maturity.

	Very short term	Short-term	Mid-term	Long-term
Out of the money	0.0019090826	0.0025499896	0.0024879919	0.0027399981
	(10.203254151)	(23.553249001)	(21.739344248)	(20.288779246)
At the money	0.0018427939	0.0015180356	0.001197288	0.0010442315
	(18.523374937)	(16.281933846)	(11.488142768)	(8.592019933)
In the money	0.000647095	0.0002116238	0.0006862334	0.0005891505
	(3.5218054041)	(1.7152557279)	(6.0146149778)	(5.3443235724)

Table A.12
Summary of Variables across Deciles of VS

I rank all firms daily on the basis of volatility skew (VS). Once the ranking is established, I calculate the mean values of the relevant variables from the pooled sample. VS represents the volatility skew. R represents the relative overvaluation in the equity market calculated as $R = 100 * \ln\left(\frac{S}{IS}\right)$. Short volume ratio is the short volume divided by daily total trading volume. σ is the estimated standard deviation of daily stock returns for the last 252 trading days. Finally DIFOPN is the difference of opinion variable measured as the standard deviation of analyst earnings forecasts.

		VS	R	Short volume ratio	σ	DIFOPN
(Low VS)	1	-0.18104	-0.18401	0.33962288	0.515041	0.002849
	2	-0.04769	0.024419	0.33395382	0.486008	0.002273
	3	-0.02461	0.088232	0.32949206	0.477785	0.002113
	4	-0.00502	0.14186	0.32801724	0.473726	0.002118
	5	0.015062	0.190001	0.32546648	0.466375	0.002084
	6	0.037829	0.240006	0.32177057	0.455077	0.002085
	7	0.065235	0.285418	0.31587121	0.43641	0.001978
	8	0.100852	0.353677	0.30885436	0.414541	0.001987
	9	0.153322	0.461479	0.30180818	0.391285	0.001891
(High VS)	10	0.29758	1.008228	0.29659852	0.386554	0.002497

Table A.13

Summary of Variables across Deciles of R

I rank all firms daily on the basis of R, measured as (100*ln(S/IS)), where S is the current stock price and IS is the option implied stock price . Once the ranking is established, I calculate the mean values of the relevant variables from the pooled sample. VS represents the volatility skew measured as the difference between the implied volatilities of OTM put options and ATM call option Short volume ratio is the short volume divided by daily total trading volume. σ is the estimated standard deviation of daily stock returns for the last 252 trading days. DIFOPN is the difference of opinion variable measured as the standard deviation of analyst earnings forecasts.

		R	VS	Short volume Ratio	σ	DIFOPN
(Low R)	1	-1.44504	0.016442	0.288915	0.438441	0.002468
	2	-0.24252	-0.00201	0.304792	0.437951	0.001932
	3	-0.0703	0.010667	0.311173	0.444923	0.00181
	4	0.044023	0.019822	0.316968	0.449834	0.001737
	5	0.142274	0.028428	0.320172	0.452902	0.001772
	6	0.241109	0.038027	0.324868	0.458437	0.001851
	7	0.356316	0.046965	0.329002	0.466874	0.002035
	8	0.511998	0.057174	0.333709	0.48022	0.002352
	9	0.789528	0.066021	0.34127	0.504428	0.002993
(High R)	10	2.260287	0.132662	0.33082	0.574858	0.005381

Table A.14

Summary of variables across Deciles of Short Volume Ratio

I rank all firms daily on the basis of short volume ratio, measured as daily short volume divided by daily total trading volume. Once the ranking is established, I calculate the mean values of the relevant variables from the pooled sample. VS represents the volatility skew measured as the difference between the implied volatilities of OTM put options and ATM call option. R represents the relative overvaluation in the equity market calculated as R=(100*ln(S/IS)). σ is the estimated standard deviation of daily stock returns for the last 252 trading days. DIFOPN is the difference of opinion variable measured as the standard deviation of analyst earnings forecasts.

		Short volume ratio	VS	R	σ	DIFOPN
(Low Short Volume)	1	0.128472	0.067994	0.24629	0.390286	0.002536
	2	0.193499	0.055952	0.212338	0.400969	0.00219
	3	0.231196	0.05388	0.209587	0.408277	0.002208
	4	0.264312	0.054564	0.212839	0.414079	0.00232
	5	0.294687	0.05131	0.224074	0.421719	0.002439
	6	0.325184	0.047451	0.234979	0.427553	0.00259
	7	0.358251	0.045845	0.236407	0.430664	0.002631
	8	0.396687	0.047965	0.254324	0.434367	0.002722
	9	0.447091	0.048643	0.256246	0.435886	0.002758
(High Short Volume)	10	0.550997	0.054333	0.258009	0.430864	0.002775

Table A.15
Portfolios Formed on the Basis of VS

Over the sample period of 2004 to 2009, at the end of each trading day, I sort stocks into 10 groups by their most recently calculated volatility skew and assign them to decile portfolios. Once the portfolios are formed, each stock is held for 1 trading day. I then compute the equally-weighted returns over the next day. The returns presented in the table are average returns over all formation periods. Decile 1 represents a portfolio consisting of firms with the lowest volatility skew and decile 10 represents a portfolio consisting firms with the highest volatility skew. The (1-10) portfolio reports the average returns of a zero investment hedge portfolio that is long the lowest VS portfolio and short the highest VS portfolio.

		Average Daily Return	Std. Error	t-stat	Prob(t)
(Low VS)	1	0.001664075	0.000529	3.147419	0.00168
	2	0.000944001	0.000485	1.946326	0.051807
	3	0.000557872	0.000468	1.192775	0.233151
	4	0.00034735	0.000456	0.762396	0.445947
	5	0.000065402	0.000442	0.147867	0.882468
	6	-7.6429E-05	0.000429	-0.17799	0.858758
	7	-0.00031639	0.000417	-0.75892	0.448021
	8	-0.00037435	0.000398	-0.93968	0.347535
	9	-0.00061715	0.000367	-1.67939	0.09329
(High VS)	10	-0.00111008	0.000348	-3.18578	0.001474
	1-10	0.002774155	0.000244	11.35877	1.03E-28

Table A.16
Portfolios Formed on the Basis of R

Over the sample period of 2004 to 2009, at the end of each trading day, I sort stocks into 10 groups by their most recently calculated value of R and assign them to decile portfolios. Once the portfolios are formed, each stock is held for 1 trading day. I then compute the equally-weighted returns over the next day. The returns presented in the table are average returns over all formation periods. Decile 1 represents a portfolio consisting of firms with the lowest R (relatively undervalued in the stock market) and decile 10 represents a portfolio consisting firms with the highest R (relatively overvalued in the stock market). The (1-10) portfolio reports the average returns of a zero investment hedge portfolio that is long the lowest R portfolio and short the highest R portfolio.

		Average Daily Return	Std. Error	t-stat	Prob(t)
(Low R)	1	0.001357	0.000458	2.964991	0.003076
	2	0.001005	0.000443	2.266454	0.02357
	3	0.000858	0.000435	1.974392	0.048526
	4	0.000575	0.000429	1.341141	0.180084
	5	0.000245	0.000432	0.566592	0.571079
	6	5.08E-06	0.000435	0.011682	0.990681
	7	-0.00011	0.000447	-0.25679	0.797374
	8	-0.0004	0.000461	-0.87231	0.383183
	9	-0.00072	0.000476	-1.52015	0.128691
(High R)	10	-0.00141	0.000524	-2.70245	0.006963
	1-10	0.002769	0.000209	13.22085	9.20E-38

Table A.17

Portfolios Formed on the Basis of Short Volume Ratio

Over the sample period of 2004 to 2009, at the end of each trading day, I sort stocks into 10 groups by their most recently calculated short volume ratio (SVR) and assign them to decile portfolios. Once the portfolios are formed, each stock is held for 1 trading day. I then compute the equally-weighted returns over the next day. The returns presented in the table are average returns over all formation periods. Decile 1 represents a portfolio consisting of firms with the lowest SVR and decile 10 represents a portfolio consisting firms with the highest SVR. The (1-10) portfolio reports the average returns of a zero investment hedge portfolio that is long the lowest SVR portfolio and short the highest SVR portfolio.

		Average Daily Return	Std. Error	t-stat	Prob(t)
(Low SVR)	1	0.000952	0.000425	2.241499	0.02515
	2	0.000667	0.000446	1.493795	0.135455
	3	0.000479	0.000447	1.072003	0.283904
	4	0.000216	0.000462	0.467087	0.64051
	5	0.000109	0.000468	0.232395	0.816265
	6	-2.5E-05	0.000478	-0.05315	0.95762
	7	6.35E-05	0.000486	0.130533	0.896163
	8	-0.00014	0.000492	-0.29292	0.769629
	9	-0.0002	0.0005	-0.39772	0.690898
(High SVR)	10	-5.1E-05	0.000497	-0.10184	0.918901
	1-10	0.000995	0.000202	4.924832	9.45E-07

Table A.18

Portfolios Formed on the Basis of Option Market Measures (VS and R)

Over the sample period of 2005 to 2009, at the end of each trading day, I sort stocks into 25 groups. For panel A, I first sort stocks into 5 portfolios based on volatility skew (VS). Next, I sort stocks in each of these portfolios into 5 groups based on their most recently calculated value of R. Once the portfolios are formed, each stock is held for 1 trading day. I then compute the equally-weighted returns over the next month. The returns presented in the panel A are average daily returns over all formation periods. For panel B, I first sort stocks into 5 portfolios based on the most recently calculated value of R. Next, I sort stocks in each of these portfolios into 5 groups based on their volatility skew (VS).

Panel A: Quintiles of R controlled by VS

		Low R				High R
		1	2	3	4	5
Low VS	1	0.002473	0.001858	0.001201	0.001014	0.000338
	2	0.001156	0.000866	0.000267	0.000217	3.18E-05
	3	0.000613	0.00037	-8.6E-05	-0.00018	-0.00049
	4	0.000269	-2.2E-05	-0.00037	-0.00078	-0.001
High VS	5	1.78E-06	-0.00031	-0.00074	-0.00134	-0.0022

Panel B: Quintiles of VS controlled by R

		Low VS				High VS
		1	2	3	4	5
Low R	1	0.002499	0.001675	0.000973	0.000497	0.000264
	2	0.001342	0.001183	0.000777	0.000355	-7.5E-05
	3	0.000868	0.000231	-0.00024	-9.3E-05	-0.00012
	4	0.000515	-7.9E-05	-0.00024	-0.00064	-0.00086
High R	5	-0.00019	-0.00048	-0.00095	-0.00147	-0.00226

Table A.19

Portfolios Formed on the Basis of Skewness and Short Volume Ratio

Over the sample period of 2005 to 2009, at the end of each trading day, I sort stocks into 25 groups. For panel A, I first sort stocks into 5 portfolios based on volatility skew (VS). Next, I sort stocks in each of these portfolios into 5 groups based on their short volume ratio (SVR). Once the portfolios are formed, each stock is held for 1 trading day. I then compute the equally-weighted returns over the next month. The returns presented in the panel A are average daily returns over all formation periods. For panel B, I first sort stocks into 5 portfolios based on SVR. Next, I sort stocks in each of these portfolios into 5 groups based on their volatility skew (VS).

Panel A: Quintiles of SVR controlled by VS

		Low SVR				High SVR
		1	2	3	4	5
Low VS	1	0.002129	0.001411	0.001303	0.000809	0.000719
	2	0.001321	0.000869	0.000252	0.000208	0.000232
	3	0.000824	0.000231	-9E-05	-6.9E-05	-0.00015
	4	0.000404	-0.00019	-0.00027	-0.00056	-0.00045
High VS	5	-7E-05	-0.00045	-0.00072	-0.0009	-0.00078

Panel B: Quintiles of VS controlled by SVR

		Low VS				High VS
		1	2	3	4	5
Low SVR	1	0.002076	0.00112	0.000693	0.000443	-0.00028
	2	0.001458	0.00086	0.000132	-0.00019	-0.00053
	3	0.00106	0.000317	-7E-05	-0.00038	-0.00072
	4	0.000816	0.000256	-4.7E-05	-0.00049	-0.00073
High SVR	5	0.000707	0.000202	-0.00023	-0.00051	-0.00078

Table A.20
Portfolios Formed on the Basis of R and Short Volume Ratio

Over the sample period of 2005 to 2009, at the end of each trading day, I sort stocks into 25 groups. For panel A, I first sort stocks into 5 portfolios based on R, measured as (100*ln(S/IS)), where S is the current stock price and IS is the option implied stock price . Next, I sort stocks in each of these portfolios into 5 groups based on their short volume ratio (SVR). Once the portfolios are formed, each stock is held for 1 trading day. I then compute the equally-weighted returns over the next month. The returns presented in the panel A are average daily returns over all formation periods. For panel B, I first sort stocks into 5 portfolios based on SVR. Next, I sort stocks in each of these portfolios into 5 groups based on the value of R.

Panel A: Quintiles of SVR controlled by R

		Low SVR				High SVR
		1	2	3	4	5
Low R	1	0.001654	0.001298	0.000954	0.00109	0.000771
	2	0.001208	0.000818	0.000523	0.00043	0.000538
	3	0.000822	0.0004	-0.00019	-0.00016	9.63E-05
	4	0.000511	-4.7E-05	-0.00019	-0.00019	-0.00033
High R	5	-0.00041	-0.00077	-0.00075	-0.00103	-0.00107

Panel B: Quintiles of R controlled by SVR

		Low R				High R
		1	2	3	4	5
Low SVR	1	0.001625	0.001116	0.000774	0.000627	-0.00047
	2	0.001053	0.000954	0.000405	0.000222	-0.00053
	3	0.000946	0.000509	2.01E-05	4.44E-05	-0.00097
	4	0.001099	0.000501	-0.00015	-0.00029	-0.00075
High SVR	5	0.000715	0.000663	-3.6E-05	-0.00026	-0.00121

Table A.21

Fama-Macbeth Regressions of Future Returns

Fama and Macbeth (1973) cross-sectional regressions are run every trading day from 2004 to 2009. One day ahead future returns (denoted as t_{t+1}) is regressed on lagged values of volatility skew and short volume ratio. VS_t , VS_{t-1} and VS_{t-2} represent contemporaneous, 1 day lagged and 2 day lagged values of volatility skew. Similarly, $\mathrm{SVR_t}$, $\mathrm{SVR_{t-1}}$ and $\mathrm{SVR_{t-2}}$ represent contemporaneous, 1 day lagged and 2 day lagged values of short volume ratio.

VARIABLES	(1) Ret_{t+1}	(2) Ret_{t+1}	(3) Ret_{t+1}
VS_t	-.0047539***	-.0057517***	-0.00606***
	(.0005287)	(.0004402)	(0.000414)
VS_{t-1}		.0016416***	0.00119***
		(.0004217)	(0.000384)
VS_{t-2}			0.00114***
			(0.000373)
$\mathrm{SVR_t}$	-.0027705***	-.0025645***	-0.00254***
	(.0004623)	(.0003977)	(0.000375)
$\mathrm{SVR_{t-1}}$		-.0005091	-0.000602*
		(.000379)	(0.000346)
$\mathrm{SVR_{t-2}}$			0.000165
			(0.000332)
Constant	.0012242***	.0013157**	0.00126***
	(.0004341)	(.0004321)	(0.000431)
Observations	1,168,307	1,164,798	1,161,388
R-squared	.0144	0.021	0.026
Number of groups	1401	1400	1,399

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.22

Fama-Macbeth Regressions of Difference in Opinions

Fama and Macbeth (1973) cross-sectional regressions are run every trading day from 2004 to 2009. DIFOPN is the difference of opinion variable measured as the standard deviation of analyst earnings forecasts. DIFOPN is regressed on contemporaneous values of R, volatility skew (VS) and short volume ratio (SVR).

VARIABLES	(1) DIFOPN
R	0.00113***
	(5.64e-05)
VS	-0.00471***
	(0.000330)
SVR	0.00125***
	(0.000126)
Constant	0.00228***
	(6.28e-05)
Observations	730,725
Number of cross-sections	1,339
R-squared	0.052

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.23
Quintiles of R controlled by VS

Panel A: Raw Returns

		Low R				High R
		1	2	3	4	5
Low VS	1	0.002499	0.001675	0.000973	0.000497	0.000264
	2	0.001342	0.001183	0.000777	0.000355	-0.000075
	3	0.000868	0.000231	-0.000244	-0.000093	-0.000124
	4	0.000515	-0.000079	-0.000243	-0.000644	-0.000861
High VS	5	-0.000186	-0.000475	-0.000949	-0.001466	-0.002263

Panel B: Market Adjusted Returns

		Low R				High R
		1	2	3	4	5
Low VS	1	0.002322	0.001568	0.000898	0.000370	0.000173
	2	0.001177	0.001076	0.000591	0.000241	-0.000181
	3	0.000668	0.000035	-0.000448	-0.000221	-0.000257
	4	0.000354	-0.000288	-0.000419	-0.000829	-0.001018
High VS	5	-0.000381	-0.000616	-0.001117	-0.001534	-0.002505

Panel C: Size and BM adjusted returns

		Low R				High R
		1	2	3	4	5
Low VS	1	0.002972	0.002819	0.003302	0.001281	-0.001235
	2	0.000463	0.002465	0.000984	0.001140	-0.000547
	3	0.001474	0.001810	0.001165	0.001203	0.000437
	4	0.001115	-0.000700	-0.002306	-0.001261	-0.001291
High VS	5	-0.000081	-0.001895	-0.000656	-0.003092	-0.004288

Panel D: 3-Factor adjusted returns

		Low R				High R
		1	2	3	4	5
Low VS	1	0.002303	0.001541	0.000901	0.000380	0.000169
	2	0.001144	0.001068	0.000588	0.000234	-0.000198
	3	0.000681	0.000026	-0.000459	-0.000239	-0.000279
	4	0.000336	-0.000321	-0.000397	-0.000831	-0.001023
High VS	5	-0.000380	-0.000612	-0.001106	-0.001528	-0.002514

Table A.23 -continued

Panel E: 4-Factor adjusted returns

		Low R				High R
		1	2	3	4	5
Low VS	1	0.002428	0.001667	0.001000	0.000477	0.000235
	2	0.001262	0.001160	0.000685	0.000311	-0.000126
	3	0.000790	0.000118	-0.000365	-0.000153	-0.000213
	4	0.000459	-0.000211	-0.000305	-0.000737	-0.000949
High VS	5	-0.000229	-0.000534	-0.001020	-0.001462	-0.002464

Table A.24
Quintiles of VS controlled by R

Panel A: Raw Returns

		Low VS				High VS
		1	2	3	4	5
Low R	1	0.002499	0.001675	0.000973	0.000497	0.000264
	2	0.001342	0.001183	0.000777	0.000355	-0.000075
	3	0.000868	0.000231	-0.000244	-0.000093	-0.000124
	4	0.000515	-0.000079	-0.000243	-0.000644	-0.000861
High R	5	-0.000186	-0.000475	-0.000949	-0.001466	-0.002263

Panel B: Market Adjusted Returns

		Low VS				High VS
		1	2	3	4	5
Low R	1	0.002322	0.001568	0.000898	0.000370	0.000173
	2	0.001177	0.001076	0.000591	0.000241	-0.000181
	3	0.000668	0.000035	-0.000448	-0.000221	-0.000257
	4	0.000354	-0.000288	-0.000419	-0.000829	-0.001018
High R	5	-0.000381	-0.000616	-0.001117	-0.001534	-0.002505

Panel C: Size and BM adjusted returns

		Low VS				High VS
		1	2	3	4	5
Low R	1	0.002972	0.002819	0.003302	0.001281	-0.001235
	2	0.000463	0.002465	0.000984	0.001140	-0.000547
	3	0.001474	0.001810	0.001165	0.001203	0.000437
	4	0.001115	-0.000700	-0.002306	-0.001261	-0.001291
High R	5	-0.000081	-0.001895	-0.000656	-0.003092	-0.004288

Panel D: 3-Factor adjusted returns

		Low VS				High VS
		1	2	3	4	5
Low R	1	0.002303	0.001541	0.000901	0.000380	0.000169
	2	0.001144	0.001068	0.000588	0.000234	-0.000198
	3	0.000681	0.000026	-0.000459	-0.000239	-0.000279
	4	0.000336	-0.000321	-0.000397	-0.000831	-0.001023
High R	5	-0.000380	-0.000612	-0.001106	-0.001528	-0.002514

Table A.24 - continued

Panel E: 4-Factor adjusted returns

		Low VS				High VS
		1	2	3	4	5
Low R	1	0.002428	0.001667	0.001000	0.000477	0.000235
	2	0.001262	0.001160	0.000685	0.000311	-0.000126
	3	0.000790	0.000118	-0.000365	-0.000153	-0.000213
	4	0.000459	-0.000211	-0.000305	-0.000737	-0.000949
High R	5	-0.000229	-0.000534	-0.001020	-0.001462	-0.002464

Table A.25
Quintiles of SVR controlled by R

Panel A: Raw Returns

		Low SVR				High SVR
		1	2	3	4	5
Low R	1	0.001654	0.001298	0.000954	0.001090	0.000771
	2	0.001208	0.000818	0.000523	0.000430	0.000538
	3	0.000822	0.000400	-0.000186	-0.000161	0.000096
	4	0.000511	-0.000047	-0.000189	-0.000190	-0.000331
High R	5	-0.000414	-0.000770	-0.000745	-0.001033	-0.001074

Panel B: Market Adjusted Returns

		Low SVR				High SVR
		1	2	3	4	5
Low R	1	0.001533	0.001223	0.000853	0.000988	0.000658
	2	0.001112	0.000711	0.000396	0.000341	0.000430
	3	0.000662	0.000276	-0.000332	-0.000279	-0.000043
	4	0.000382	-0.000199	-0.000374	-0.000358	-0.000509
High R	5	-0.000683	-0.000975	-0.000937	-0.001293	-0.001305

Panel C: Size and BM adjusted returns

		Low SVR				High SVR
		1	2	3	4	5
Low R	1	0.003284	0.001729	0.002974	0.000231	0.002400
	2	-0.000214	0.003230	0.000498	0.002924	-0.000608
	3	0.001414	0.003936	0.001318	-0.000674	-0.000081
	4	-0.000233	-0.000448	-0.000429	-0.001540	-0.001468
High R	5	-0.000725	-0.002947	-0.001462	-0.003836	-0.002613

Panel D: 3-Factor adjusted returns

		Low SVR				High SVR
		1	2	3	4	5
Low R	1	0.001514	0.001231	0.000844	0.000950	0.000666
	2	0.001056	0.000685	0.000414	0.000332	0.000403
	3	0.000633	0.000230	-0.000331	-0.000304	-0.000058
	4	0.000348	-0.000219	-0.000410	-0.000372	-0.000531
High R	5	-0.000706	-0.000934	-0.000971	-0.001299	-0.001328

Table A.25 - continued

Panel E: 4-Factor adjusted returns

		Low SVR				High SVR
		1	2	3	4	5
Low R	1	0.001579	0.001333	0.000946	0.001058	0.000789
	2	0.001100	0.000745	0.000512	0.000427	0.000517
	3	0.000695	0.000313	-0.000248	-0.000195	0.000078
	4	0.000410	-0.000158	-0.000322	-0.000264	-0.000432
High R	5	-0.000654	-0.000817	-0.000866	-0.001179	-0.001220

Table A.26
Quintiles of R controlled by SVR

Panel A: Raw Returns

		Low R 1	2	3	4	HighR 5
Low SVR	1	0.001625	0.001116	0.000774	0.000627	-0.000467
	2	0.001053	0.000954	0.000405	0.000222	-0.000534
	3	0.000946	0.000509	0.000020	0.000044	-0.000966
	4	0.001099	0.000501	-0.000147	-0.000294	-0.000748
High SVR	5	0.000715	0.000663	-0.000036	-0.000261	-0.001210

Panel B: Market Adjusted Returns

		Low R 1	2	3	4	High R 5
Low SVR	1	0.001529	0.001010	0.000638	0.000446	-0.000761
	2	0.000950	0.000852	0.000299	0.000072	-0.000719
	3	0.000845	0.000384	-0.000124	-0.000108	-0.001215
	4	0.000996	0.000425	-0.000260	-0.000473	-0.000968
High SVR	5	0.000574	0.000566	-0.000181	-0.000463	-0.001468

Panel C: Size and BM adjusted returns

		Low R 1	2	3	4	High R 5
Low SVR	1	0.002475	-0.000606	0.001148	-0.001107	-0.000887
	2	0.002407	0.002772	0.000539	0.000199	-0.002002
	3	0.001343	0.001910	0.001366	-0.000310	-0.001715
	4	0.000043	0.002341	0.001043	-0.000196	-0.002421
High SVR	5	0.001917	-0.001514	-0.001194	-0.001038	-0.002959

Panel D: 3-Factor adjusted returns

		Low R 1	2	3	4	High R 5
Low SVR	1	0.001517	0.000989	0.000606	0.000384	-0.000762
	2	0.000927	0.000871	0.000266	0.000035	-0.000691
	3	0.000832	0.000374	-0.000135	-0.000144	-0.001195
	4	0.000965	0.000417	-0.000266	-0.000505	-0.000993
High SVR	5	0.000574	0.000554	-0.000195	-0.000504	-0.001489

Table A.26 - continued

Panel E: 4-Factor adjusted returns

		Low R				High R
		1	2	3	4	5
Low SVR	1	0.001597	0.001024	0.000658	0.000457	-0.000717
	2	0.001024	0.000955	0.000346	0.000099	-0.000586
	3	0.000913	0.000441	-0.000052	-0.000085	-0.001055
	4	0.001086	0.000526	-0.000159	-0.000391	-0.000881
High SVR	5	0.000692	0.000689	-0.000072	-0.000405	-0.001361

Table A.27
Quintiles of VS controlled by SVR

Panel A: Raw Returns

		Low VS				High VS
		1	2	3	4	5
Low SVR	1	0.002076	0.00112	0.000693	0.000443	-0.00028
	2	0.001458	0.00086	0.000132	-0.00019	-0.00053
	3	0.00106	0.000317	-7E-05	-0.00038	-0.00072
	4	0.000816	0.000256	-4.7E-05	-0.00049	-0.00073
High SVR	5	0.000707	0.000202	-0.00023	-0.00051	-0.00078

Panel B: Market Adjusted Returns

		Low VS				High VS
		1	2	3	4	5
Low SVR	1	0.001962	0.000977	0.000565	0.000327	-0.000494
	2	0.001337	0.000730	-0.000038	-0.000300	-0.000673
	3	0.000934	0.000105	-0.000197	-0.000487	-0.000915
	4	0.000692	0.000130	-0.000196	-0.000646	-0.000905
High SVR	5	0.000551	0.000018	-0.000376	-0.000706	-0.000947

Panel C: Size and BM adjusted returns

		Low VS				High VS
		1	2	3	4	5
Low SVR	1	0.002714	-0.001420	0.002567	0.001267	-0.002517
	2	0.000860	0.003804	-0.001968	0.003107	-0.001126
	3	0.004972	-0.001303	-0.000695	0.000363	-0.001344
	4	-0.000086	0.003148	0.001963	-0.002599	-0.001142
High SVR	5	0.001590	-0.002564	0.002239	-0.004949	-0.002011

Panel D: 3-Factor adjusted returns

		Low VS				High VS
		1	2	3	4	5
Low SVR	1	0.001993	0.000960	0.000588	0.000341	-0.000492
	2	0.001332	0.000738	-0.000043	-0.000299	-0.000667
	3	0.000902	0.000110	-0.000199	-0.000483	-0.000906
	4	0.000674	0.000094	-0.000198	-0.000648	-0.000904
High SVR	5	0.000539	0.000003	-0.000389	-0.000714	-0.000951

Table A.27 - continued

Panel E: 4-Factor adjusted returns

		Low VS				High VS
		1	2	3	4	5
Low SVR	1	0.002073	0.001003	0.000650	0.000382	-0.000466
	2	0.001433	0.000812	0.000039	-0.000220	-0.000600
	3	0.001017	0.000184	-0.000117	-0.000423	-0.000842
	4	0.000797	0.000195	-0.000132	-0.000578	-0.000818
High SVR	5	0.000675	0.000113	-0.000300	-0.000643	-0.000870

Table A.28
Quintiles of SVR controlled by VS

Panel A: Raw Returns

		Low SVR				High SVR
		1	2	3	4	5
Low VS	1	0.002129	0.001411	0.001303	0.000809	0.000719
	2	0.001321	0.000869	0.000252	0.000208	0.000232
	3	0.000824	0.000231	-0.000090	-0.000069	-0.000151
	4	0.000404	-0.000190	-0.000269	-0.000563	-0.000455
High VS	5	-0.000070	-0.000447	-0.000722	-0.000905	-0.000775

Panel B: Market Adjusted Returns

		Low SVR				High SVR
		1	2	3	4	5
Low VS	1	0.002020	0.001262	0.001172	0.000697	0.000580
	2	0.001196	0.000746	0.000045	0.000065	0.000071
	3	0.000714	0.000072	-0.000246	-0.000197	-0.000299
	4	0.000300	-0.000329	-0.000381	-0.000726	-0.000652
High VS	5	-0.000277	-0.000575	-0.000909	-0.001066	-0.000946

Panel C: Size and BM adjusted returns

		Low SVR				High SVR
		1	2	3	4	5
Low VS	1	0.002624	0.002206	0.003064	0.000337	0.002727
	2	0.000662	0.001156	-0.000515	0.003179	-0.001513
	3	-0.000285	-0.000320	0.000943	0.002370	-0.001024
	4	0.001125	0.002237	0.001242	-0.003928	-0.002935
High VS	5	-0.002590	-0.001929	-0.001970	-0.001250	-0.001626

Panel D: 3-Factor adjusted returns

		Low SVR				High SVR
		1	2	3	4	5
Low VS	1	0.002019	0.001255	0.001138	0.000683	0.000570
	2	0.001217	0.000754	0.000042	0.000030	0.000055
	3	0.000720	0.000059	-0.000244	-0.000206	-0.000304
	4	0.000320	-0.000321	-0.000383	-0.000728	-0.000664
High VS	5	-0.000282	-0.000559	-0.000907	-0.001063	-0.000950

Table A.28 - continued

Panel E: 4-Factor adjusted returns

		Low VS				High VS
		1	2	3	4	5
Low VS	1	0.002103	0.001350	0.001248	0.000812	0.000706
	2	0.001269	0.000840	0.000119	0.000117	0.000145
	3	0.000783	0.000141	-0.000178	-0.000117	-0.000207
	4	0.000369	-0.000257	-0.000314	-0.000658	-0.000603
High VS	5	-0.000266	-0.000487	-0.000839	-0.000988	-0.000871

Table A.29
Option Implied Volatilities and Measures of Skewness

This table reports the summary statistics of two measures of volatility skew and associated implied volatilities of put and call options, across quintiles of the volatility skew measure. The reported values are calculated using data from 1996 to 2010, and based on individual equity options available in the OptionMetrics database. Panel A, reports the local measure of volatility skew, calculated by using the equation $VS_{i,t}^{LOCAL} = IV_{i,t}^{PUT}(-.5) - IV_{i,t}^{CALL}(.5)$. Panel B, reports the right side measure of volatility skew, calculated by using the equation $VS_{i,t}^{RIGHT} = IV_{i,t}^{OTM\_CALL} - IV_{i,t}^{ATM\_CALL}$.

Panel A: Local Measure of Volatility Skew

		VS^{LOCAL}	$IV^{CALL}(.5)$	$IV^{PUT}(-.5)$
Low VS^{LOCAL}	1	-0.041	0.569	0.527
		(-0.055)	(0.258)	(0.240)
	2	-0.005	0.464	0.459
		(0.008)	(0.215)	(0.214)
	3	0.007	0.446	0.453
		(0.006)	(0.210)	(0.211)
	4	0.020	0.465	0.485
		(0.011)	(0.219)	(0.223)
High VS^{LOCAL}	5	0.065	0.528	0.593
		(0.066)	(0.252)	(0.276)

Panel B: Right Side Measure of Volatility Skew

		VS^{RIGHT}	IV^{ATM_CALL}	IV^{OTM_CALL}
Low VS^{RIGHT}	1	-0.048	0.577	0.529
		(0.060)	(0.235)	(0.211)
	2	-0.009	0.496	0.488
		(0.029)	(0.204)	(0.196)
	3	0.019	0.462	0.482
		(0.036)	(0.200)	(0.193)
	4	0.060	0.423	0.483
		(0.049)	(0.199)	(0.190)
High VS^{RIGHT}	5	0.160	0.366	0.526
		(0.120)	(0.194)	(0.211)

Table A.30
Local and Right Side Skewness across Quintiles of Fear Premium

This table reports the summary statistics of the fear premium, and the associated measures of volatility skew, over quintiles of fear premium. The reported values are calculated using data from 1996 to 2010, and based on individual equity options available in the OptionMetrics database. Here VS^{LOCAL} is the local skewness of the implied volatility smile, and VS^{RIGHT} is the right side skewness of the implied volatility smile.

		(1) Average Fear	(2) VS^{LOCAL}	(3) VS^{RIGHT}
Low Fear	1	-0.0396	0.0128	-0.0301
		(1.2660)	(0.0515)	(0.0982)
	2	-0.0139	0.0087	-0.0084
		(0.0208)	(0.0424)	(0.0871)
	3	0.0041	0.0079	0.0091
		(0.0236)	(0.0445)	(0.0943)
	4	0.0288	0.0079	0.0329
		(0.0324)	(0.0478)	(0.1075)
High Fear	5	0.0931	0.0082	0.0905
		(0.5686)	(0.0622)	(0.1382)

Table A.31

Returns on Short Option Positions on the S&P 500 Index (10% OTM)

This table reports average return on short put option positions written on the S&P 500 index, across quintiles formed on fear premium. The short put options are approximately 10% out of money and time to expiry is between 30 to 90 days. Quintile 1 represents days with low fear and quintile 5 represents days with high fear. The (5-1) portfolio represents a spread portfolio that takes long positions on low fear days and short positions oh high fear days. The reported average returns are returns over the remaining life of the shorted options. Returns on Panel A ignore transaction costs while returns on panel B consider transactions cost.

Panel A: Returns ignoring transactions costs

	Fear Rank	Average Return	t-stat
Low Fear	1	0.3223	0.8845
	2	0.4781	1.6578
	3	0.5955	2.9823
	4	0.7147	5.2562
High Fear	5	0.7736	6.6845
	5 - 1	0.6063	2.6242

Panel B: Returns with transactions costs

	Fear Rank	Average Return	t-stat
	1	0.1319	0.2726
Low Fear	2	0.3413	0.9039
	3	0.5294	2.1990
	4	0.6598	3.9265
High Fear	5	0.7333	5.2171
	5 - 1	0.4550	2.6691

Table A.32

Returns on Short Option Positions on the S&P 500 Index (5% OTM)

This table reports average return on short put option positions written on the S&P 500 index, across quintiles formed on fear premium. The short put options are approximately 5% out of money and time to expiry is between 30 to 90 days. Quintile 1 represents days with low fear and quintile 5 represents days with high fear. The (5-1) portfolio represents a spread portfolio that takes long positions on low fear days and short positions oh high fear days. The reported average returns are returns over the remaining life of the shorted options. Returns on Panel A ignore transaction costs while returns on panel B consider transactions cost.

Panel A: Returns ignoring transactions costs

	Fear Rank	Average Return	t-stat
Low Fear	1	0.3625	1.2395
	2	0.4913	2.0576
	3	0.5747	3.3140
	4	0.6743	5.2887
High Fear	5	0.7454	6.8449
	5 - 1	0.4859	2.7682

Panel B: Returns with transactions costs

	Fear Rank	Average Return	t-stat
Low Fear	1	0.2300	0.6215
	2	0.3916	1.3078
	3	0.5227	2.5953
	4	0.6282	4.1561
High Fear	5	0.7116	5.5909
	5 - 1	0.3864	2.83038

Table A.33
Number of Tail Events (VaR violations) over Fear Ranks

This table reports the number of 99% tail violations for the S&P 500 index across quintiles formed on fear premium. Quintile 1 represents days with low fear and quintile 5 represents days with high fear. The 99% Value-at-Risk (VaR) is calculated using a normal distribution. The multiple day VaR measure is created by scaling the 1-day VaR by $\sqrt{t}$, where t represents the holding period. The number of tail violations is calculated by counting occurrences of return on the index larger than the 99% VaR. For each fear rank quintile, the numbers of tail violations are reported. The table presents number of violations over 30, 60, and 90 days. Since the options strategy sells options 30 to 90 day options, I look at violation of 30, 60 . and 90 day VaRs.

	Fear Rank	30 day	60 day	90 day
Low Fear	1	1	2	2
	2	1	0	3
	3	0	0	0
	4	0	0	0
High Fear	5	0	0	0

Table A.34

Put Option Portfolios Formed on the Basis of Fear Premium

Over the sample period of 1996 to 2010, at the end of each trading day, I sort securities into 5 groups by their most recently calculated value of fear premium. Once the sorting is complete, short put option portfolios are constructed. Quintile 1 consists of options written on stocks with the lowest fear score and quintile 5 consists of options written on stocks with highest fear score. Each short put option portfolio is held till expiration. Next, equally-weighted returns over the life of the options are calculated for each fear quintile. The returns presented in the table are average returns on these portfolios over all formation periods. The (5 -1) portfolio reports the average returns of a spread portfolio that is long put options on low fear equities and short put options on high fear equities. Panel A reports returns of the strategy when OTM options are used. Panel B and panel C reports returns of the strategy when ATM and ITM options are used respectively.

Panel A: Out-of-the-money Put Options

		Average Return	Std. Error	t-stat	Prob(t)
Low Fear	1	0.0073	0.0072	1.0153	0.3100
	2	0.0331	0.0064	5.1771	0.0000
	3	0.0384	0.0063	6.1106	0.0000
	4	0.0441	0.0058	7.6187	0.0000
High Fear	5	0.0634	0.0053	11.8792	0.0000
	5-1	0.0561	0.0043	13.1484	0.0000

Panel B: At-the-money Put Options

		Average Return	Std. Error	t-stat	Prob(t)
Low Fear	1	0.0867	0.0127	6.8039	0.0000
	2	0.0877	0.0121	7.2272	0.0000
	3	0.0888	0.0127	6.9769	0.0000
	4	0.1020	0.0127	8.0330	0.0000
High Fear	5	0.1312	0.0134	9.8006	0.0000
	5-1	0.0445	0.0074	5.9959	0.0000

Panel C: In-the-money Put Options

		Average Return	Std. Error	t-stat	Prob(t)
Low Fear	1	0.2321	0.0208	11.1326	0.0000
	2	0.1501	0.0226	6.6562	0.0000
	3	0.1178	0.0251	4.6961	0.0000
	4	0.1252	0.0256	4.8968	0.0000
High Fear	5	0.1873	0.0241	7.7810	0.0000
	5-1	-0.0448	0.0162	-2.7719	0.0056

Table A.35
Call Option Portfolios Formed on the Basis of Fear premium

Over the sample period of 1996 to 2010, at the end of each trading day, I sort securities into 5 groups by their most recently calculated value of fear premium. Once the sorting is complete, short call option portfolios are constructed. Quintile 1 consists of options written on stocks with the lowest fear score and quintile 5 consists of options written on stocks with highest fear score. Each short call option portfolio is held till expiration. Next, equally-weighted returns over the life of the options are calculated for each fear quintile. The returns presented in the table are average returns on these portfolios over all formation periods. The (5 -1) portfolio reports the average returns of a spread portfolio that is long call options on low fear equities and short call options on high fear equities. Panel A reports returns of the strategy when OTM options are used. Panel B and panel C reports returns of the strategy when ATM and ITM options are used respectively.

Panel A: Out-of-the-money Call Options

		Average Return	Std. Error	t-stat	Prob(t)
Low Fear	1	0.1108	0.0193	5.7381	0.0000
	2	0.0959	0.0182	5.2549	0.0000
	3	0.1245	0.0173	7.1950	0.0000
	4	0.1312	0.0159	8.2469	0.0000
High Fear	5	0.2241	0.0134	16.7594	0.0000
	Q5-Q1	0.1133	0.0154	7.3342	0.0000

Panel B: At-the-money Call Options

		Average Return	Std. Error	t-stat	Prob(t)
Low Fear	1	0.03270	0.01164	2.80790	0.00502
	2	-0.00572	0.01103	-0.51810	0.60444
	3	-0.02183	0.01053	-2.07390	0.03816
	4	-0.02598	0.01023	-2.54050	0.01111
High Fear	5	-0.06304	0.01095	-5.75570	0.00000
	Q5-Q1	-0.09574	0.00817	-11.72160	0.00000

Panel C: In-the-money Call Options

		Average Return	Std. Error	t-stat	Prob(t)
Low Fear	1	0.00726	0.00708	1.02530	0.30530
	2	-0.01259	0.00668	-1.88450	0.05959
	3	-0.01223	0.00638	-1.91740	0.05527
	4	-0.02641	0.00596	-4.43360	0.00001
High Fear	5	-0.04079	0.00555	-7.35270	0.00000
	Q5-Q1	-0.04805	0.00437	-11.00650	0.00000

Table A.36

Put Option Portfolios Formed on the Basis of Fear premium (with transactions cost)

Over the sample period of 1996 to 2010, at the end of each trading day, I sort securities into 5 groups by their most recently calculated value of fear premium. Once the sorting is complete, short put option portfolios are constructed while considering the bid-ask spread. Quintile 1 consists of options written on stocks with the lowest fear score and quintile 5 consists of options written on stocks with highest fear score. Each short put option portfolio is held till expiration. Next, equally-weighted returns over the life of the options are calculated for each fear quintile. The returns presented in the table are average returns on these portfolios over all formation periods. The (5 -1) portfolio reports the average returns of a spread portfolio that is long put options on low fear equities and short put options on high fear equities. Panel A reports returns of the strategy when OTM options are used. Panel B and panel C reports returns of the strategy when ATM and ITM options are used respectively.

Panel A: Out-of-the-money Put Options

		Average	Std. Error	t-stat	Prob(t)
Low Fear	1	-0.0194	0.0075	-2.5859	0.0098
	2	0.0084	0.0066	1.2712	0.2037
	3	0.0118	0.0065	1.8221	0.0685
	4	0.0150	0.0060	2.5029	0.0124
High Fear	5	0.0269	0.0056	4.8259	0.0000
	5-1	0.0463	0.0045	10.2266	0.0000

Panel B: At-the-money Put Options

		Average	Std. Error	t-stat	Prob(t)
Low Fear	1	0.0340	0.0136	2.5061	0.0123
	2	0.0266	0.0131	2.0323	0.0422
	3	0.0176	0.0139	1.2658	0.2057
	4	0.0125	0.0143	0.8714	0.3836
High Fear	5	-0.0202	0.0164	-1.2283	0.2194
	5-1	-0.0542	0.0092	-5.9158	0.0000

Panel C: In-the-money Put Options

		Average	Std. Error	t-stat	Prob(t)
Low Fear	1	0.0568	0.0264	2.1557	0.0312
	2	-0.1037	0.0307	-3.3756	0.0007
	3	-0.1642	0.0339	-4.8390	0.0000
	4	-0.2219	0.0365	-6.0789	0.0000
High Fear	5	-0.3212	0.0406	-7.9186	0.0000
	5-1	-0.3780	0.0300	-12.6132	0.0000

Table A.37

Call Option Portfolios Formed on the Basis of Fear premium (with transactions cost)

Over the sample period of 1996 to 2010, at the end of each trading day, I sort securities into 5 groups by their most recently calculated value of fear premium. Once the sorting is complete, short call option portfolios are constructed while considering the bid-ask spread in options. Quintile 1 consists of options written on stocks with the lowest fear score and quintile 5 consists of options written on stocks with highest fear score. Each short call option portfolio is held till expiration. Next, equally-weighted returns over the life of the options are calculated for each fear quintile. The returns presented in the table are average returns on these portfolios over all formation periods. The (5 -1) portfolio reports the average returns of a spread portfolio that is long call options on low fear equities and short call options on high fear equities. Panel A reports returns of the strategy when OTM options are used. Panel B and panel C reports returns of the strategy when ATM and ITM options are used respectively.

Panel A: Out-of-the-money Call Options

		Average Return	Std. Error	t-stat	Prob(t)
Low Fear	1	-0.1200	0.0247	-4.8485	0.0000
	2	-0.1591	0.0240	-6.6207	0.0000
	3	-0.1846	0.0245	-7.5291	0.0000
	4	-0.2472	0.0252	-9.8255	0.0000
High Fear	5	-0.4004	0.0290	-13.7990	0.0000
	Q5-Q1	-0.2868	0.0262	-10.9314	0.0000

Panel B: At-the-money Call Options

		Average Return	Std. Error	t-stat	Prob(t)
Low Fear	1	-0.0291	0.0125	-2.3355	0.0196
	2	-0.0782	0.0120	-6.5347	0.0000
	3	-0.1110	0.0117	-9.5204	0.0000
	4	-0.1449	0.0120	-12.0844	0.0000
High Fear	5	-0.2865	0.0145	-19.7234	0.0000
	Q5-Q1	-0.2574	0.0103	-25.0933	0.0000

Panel C: In-the-money Call Options

		Average Return	Std. Error	t-stat	Prob(t)
Low Fear	1	-0.0186	0.0073	-2.5574	0.0106
	2	-0.0391	0.0069	-5.6943	0.0000
	3	-0.0414	0.0066	-6.2979	0.0000
	4	-0.0597	0.0062	-9.6744	0.0000
High Fear	5	-0.0866	0.0059	-14.7368	0.0000
	Q5-Q1	-0.0680	0.0045	-14.9904	0.0000

APPENDIX B

ILLUSTRATIONS

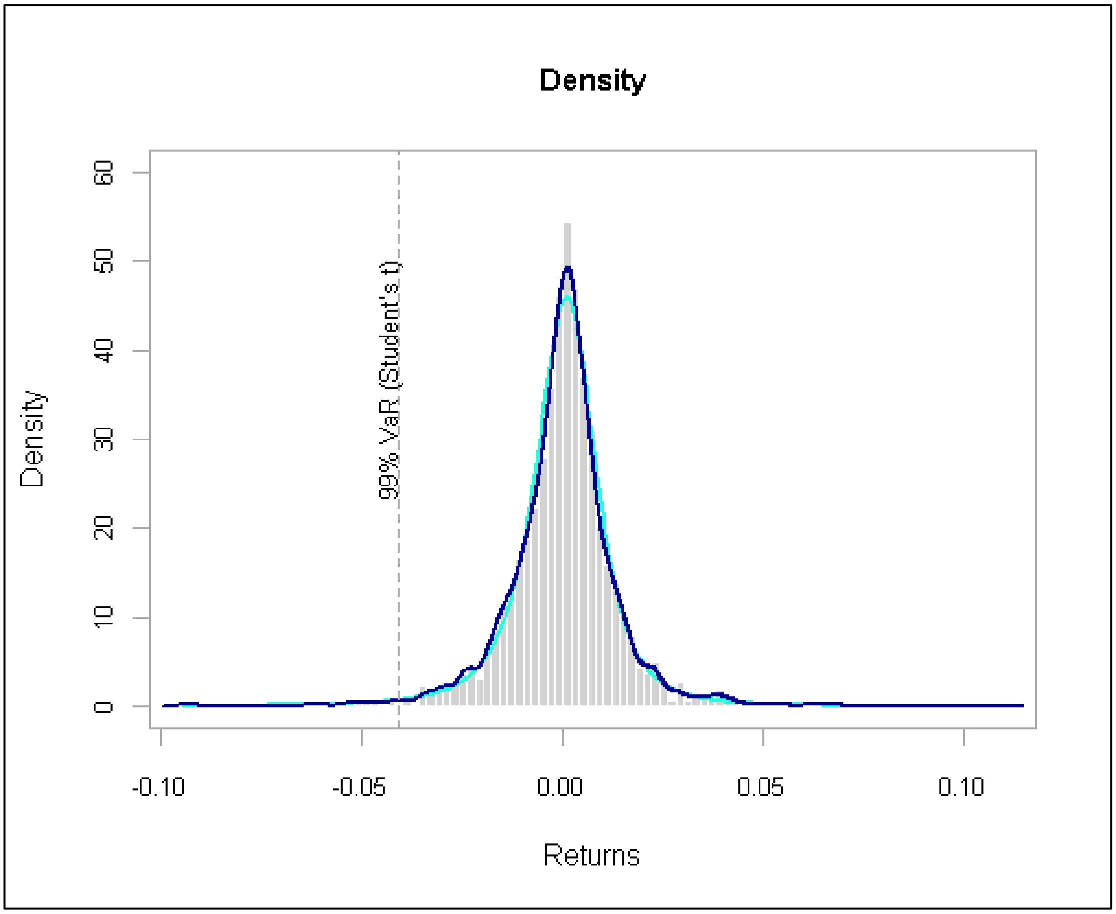

Figure B.1: Distribution of S&P 500 Returns

The dark blue line represents the kernel density function. The cyan line is the fitted t-distribution. The vertical dashed line represents the 1-day Value-at-Risk level based on the fitted t-distribution.

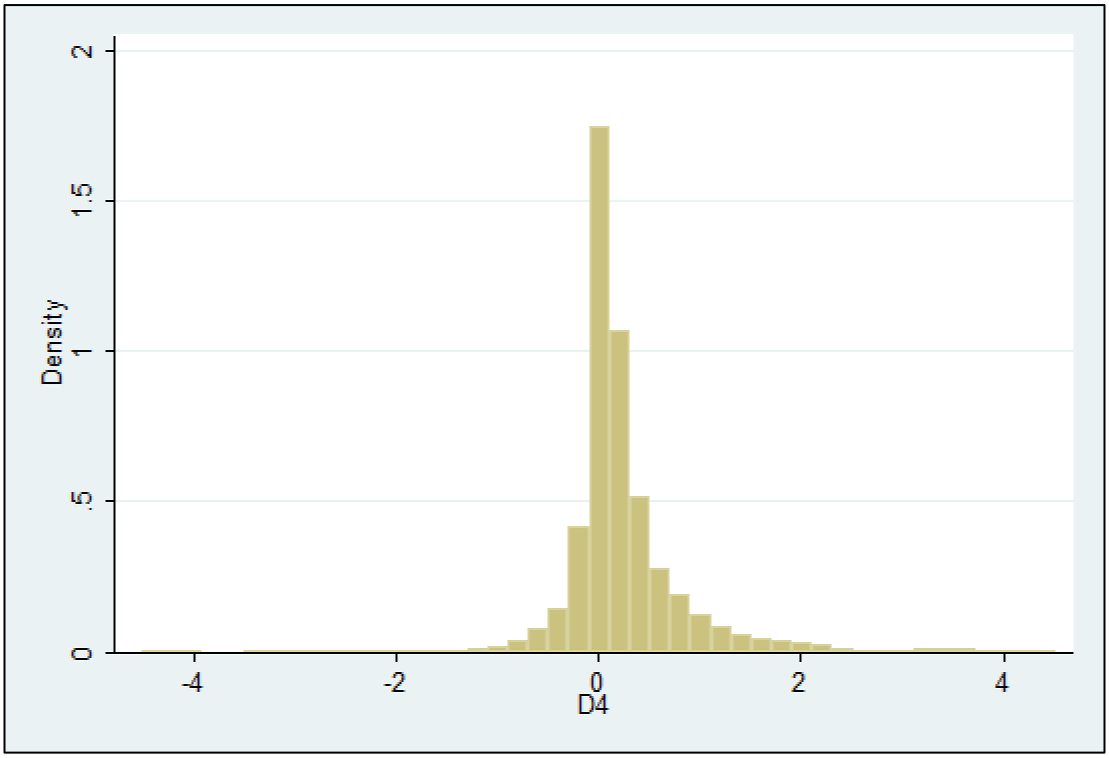

Figure B.2: Distribution of Divergence

The distribution of divergence is calculated based on daily equity observations from 2004 to 2009.

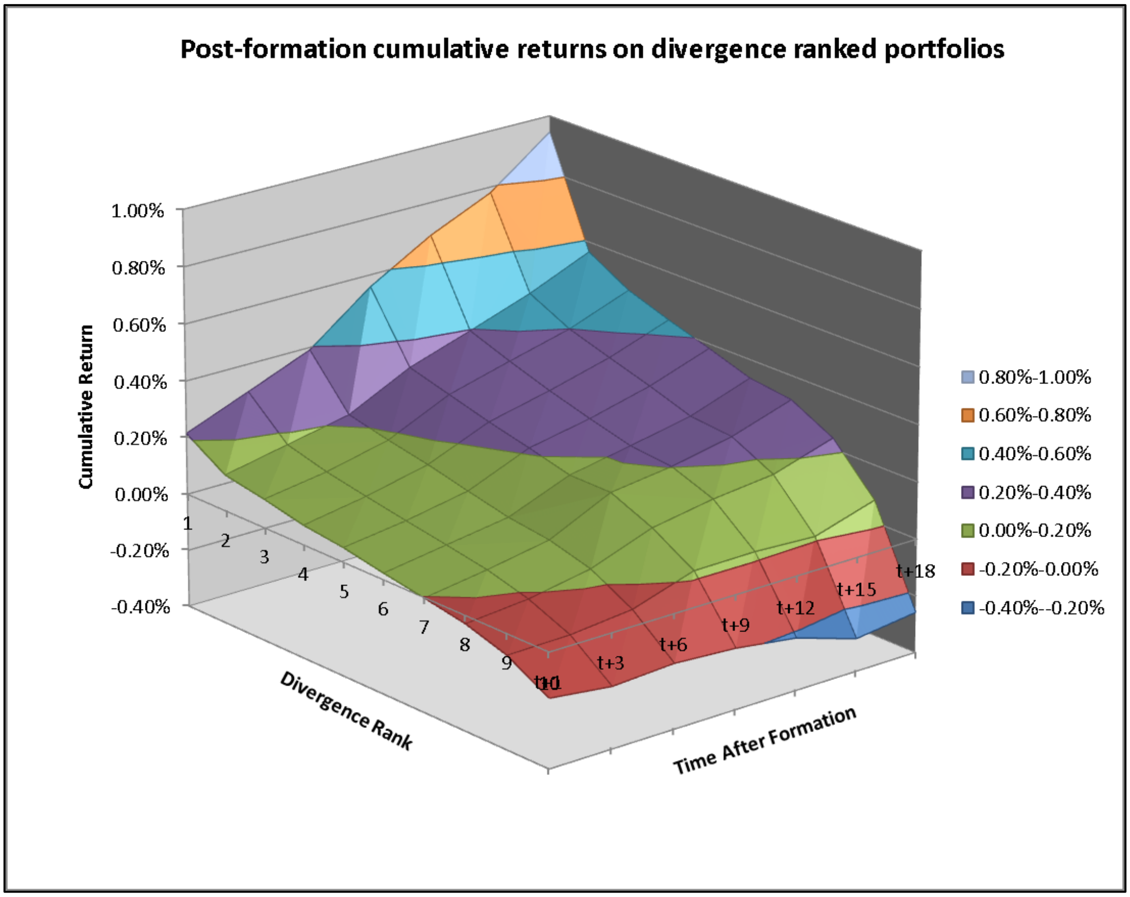

Figure B.3: Divergence Portfolio Cumulative Returns.

The figure shows average cumulative portfolio returns for all 10 divergence deciles for holding periods of 1, 3, 6, 9, 12, 15 and 18 days.

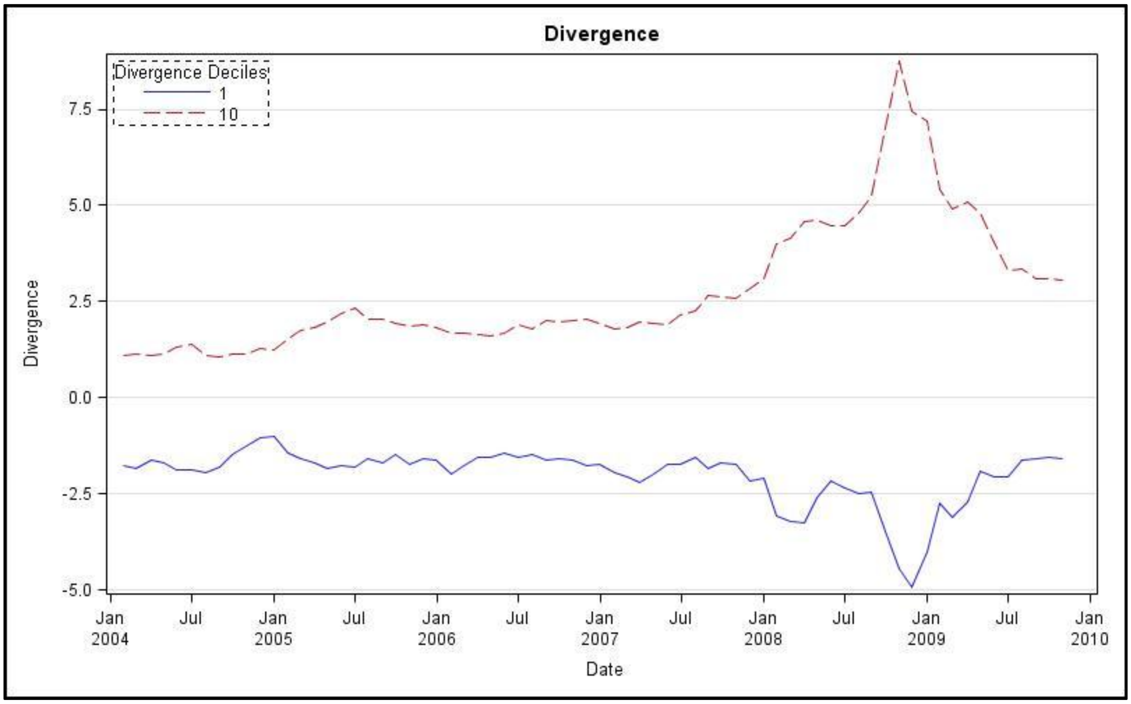

Figure B.4: Divergence Measure of the Extreme Deciles over Time.

The solid blue line represents the divergence measure for the lowest divergence decile (upward pressure). The red dashed line represents divergence measure for the highest divergence decile (downward pressure).

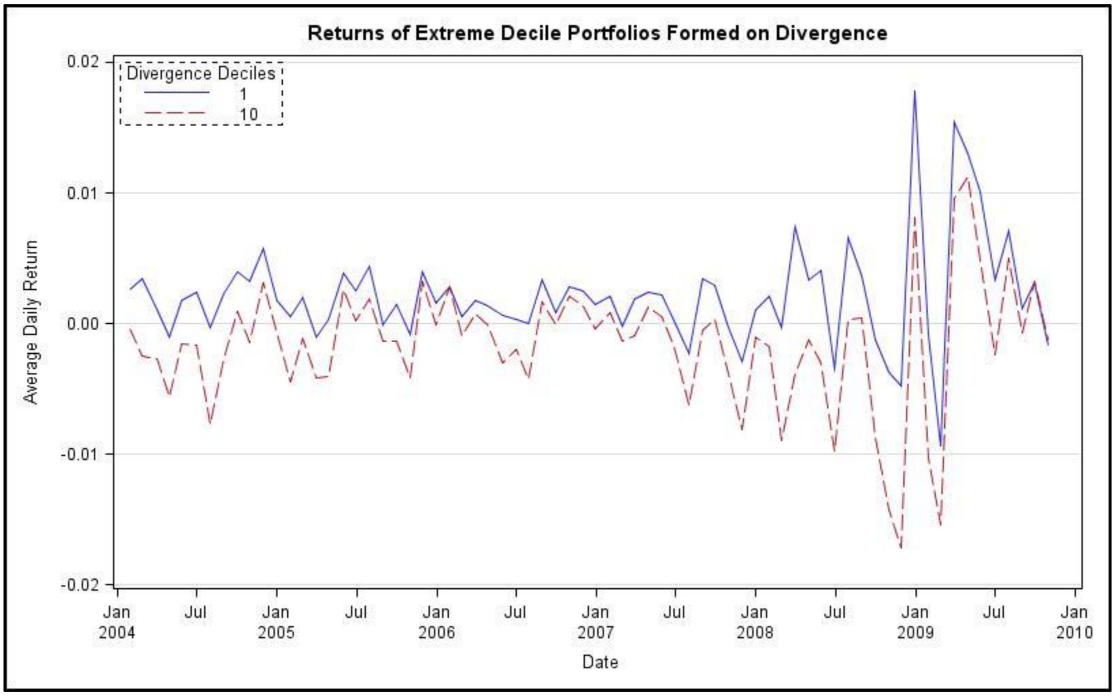

Figure B.5: Returns of Extreme Decile Portfolios Formed on Divergence.

The returns are averages daily returns for each month from March 2004 to October 2009. The solid blue line represents the returns for the lowest divergence portfolio (upward pressure). The red dashed line represents divergence measure for the highest divergence portfolio (downward pressure).

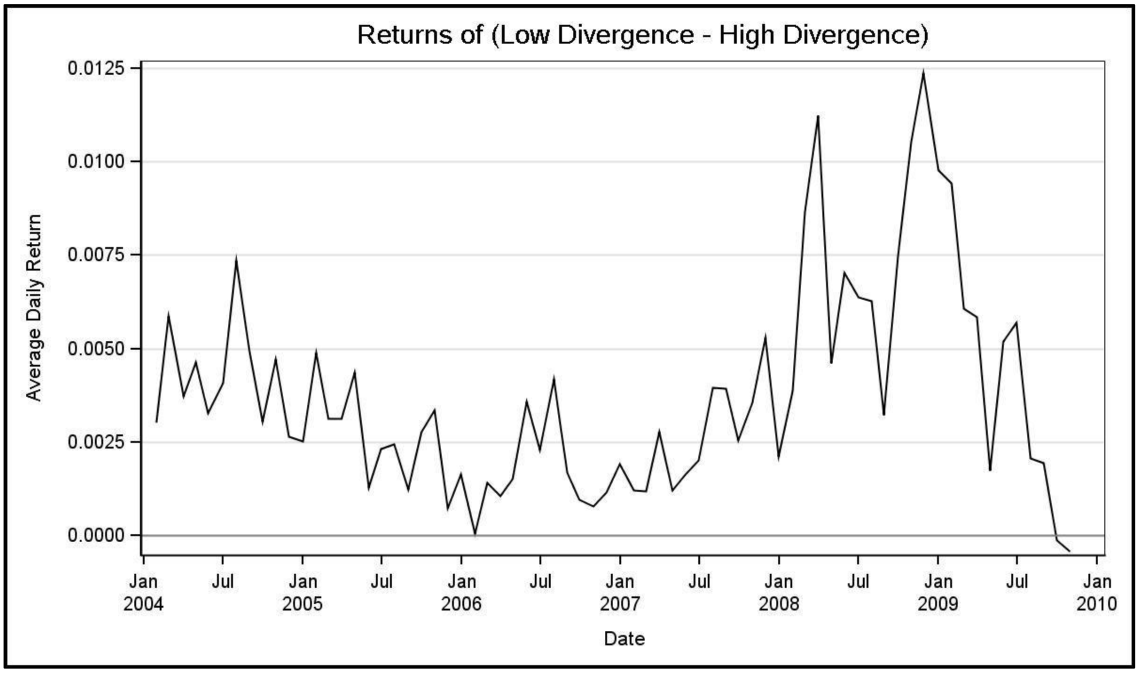

Figure B.6: Returns on Hedge Portfolio based on Divergence.

The returns are average daily returns for each month from March 2004 to October 2009. The solid black line represents the returns for the hedge portfolio that is long the lowest divergence portfolio (upward pressure) and short the highest divergence portfolio (downward pressure).

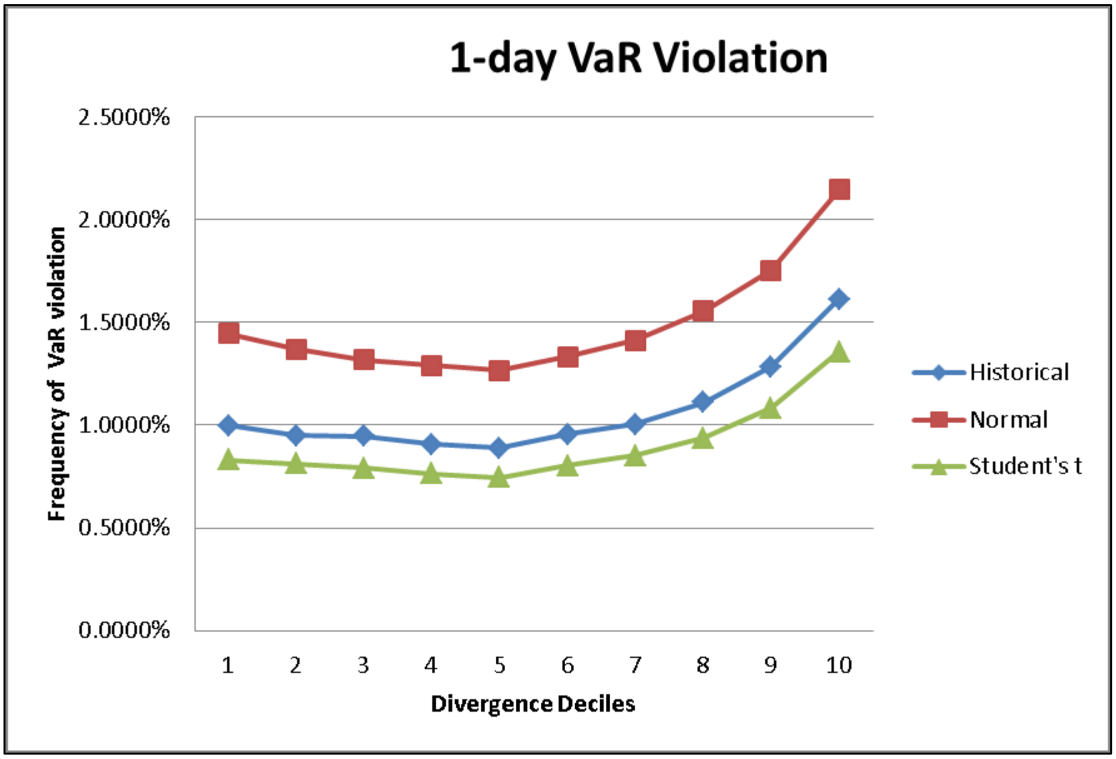

Figure B.7: Frequency of Tail Events over a 1-day Period.

The figure shows the percentage of tail violations over the 10 divergence portfolios. Three different value-at-risk or VaR models are used to identify tail violations over a 1 day holding period. The red line shows tail violation percentages when tail violations are classified using normal distribution. The green line shows tail violation percentages when tail violations are classified using a student's t-distribution. The blue line shows tail violations percentages when tail violations are classified using a historical simulation VaR.

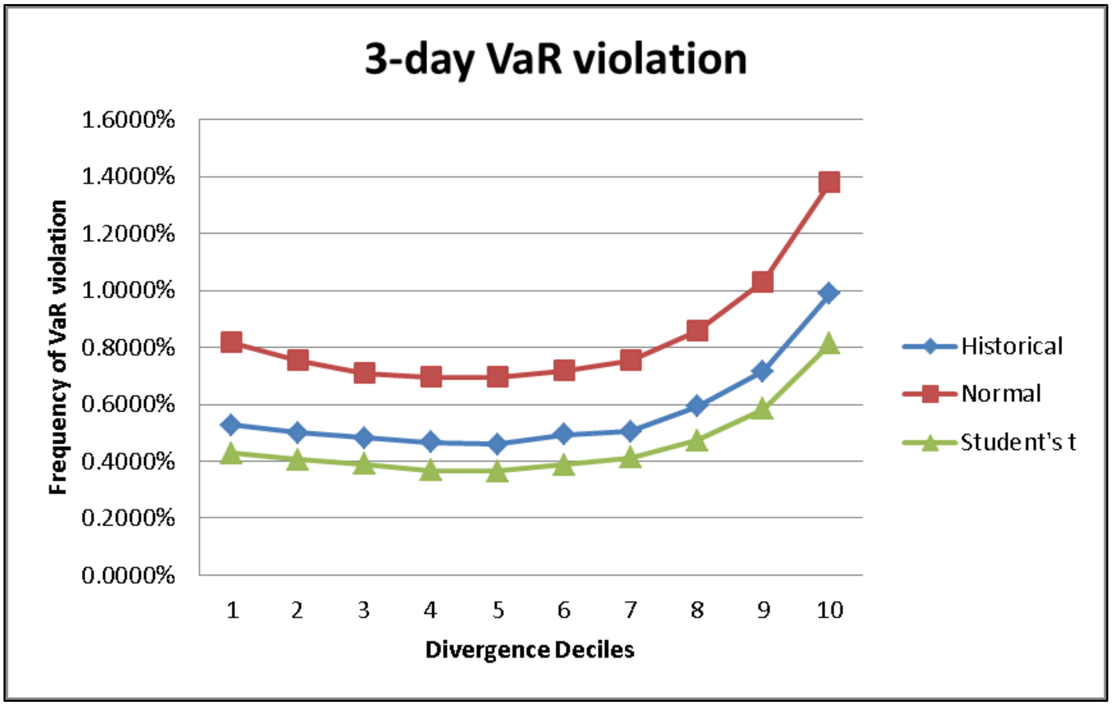

Figure B.8: Frequency of Tail Events over a 3-day Period

The figure shows the percentage of tail violations over the 10 divergence portfolios. Three different value-at-risk or VaR models are used to identify tail violations over a 3 day holding period. The red line shows tail violation percentages when tail violations are classified using a normal distribution. The green line shows tail violations percentages when tail violations are classified using a student's t-distribution. The blue line shows tail violation percentages when tail violations are classified using a historical simulation VaR.

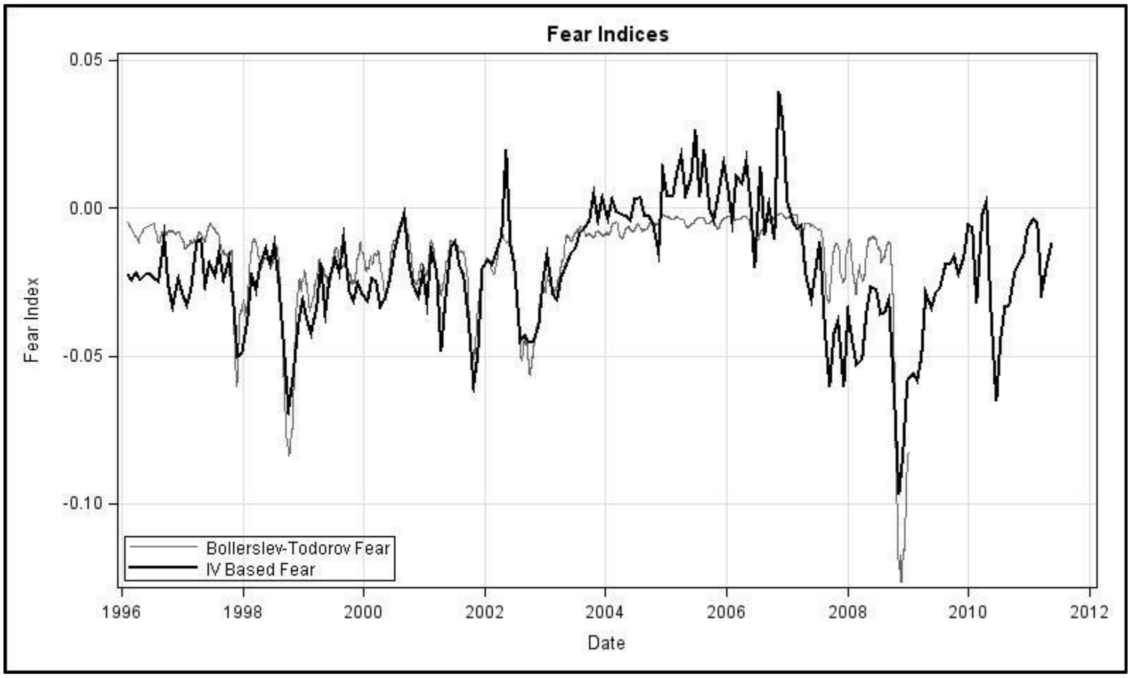

Figure B.9: Fear Index
The figure shows the estimated value of the fear premium from S&P 500 index options over January 1996 to October 2011. The dark black line is implied volatility based fear measure developed in this study. The lighter black line is the Bollerslev and Todorov (2011) measure of fear.

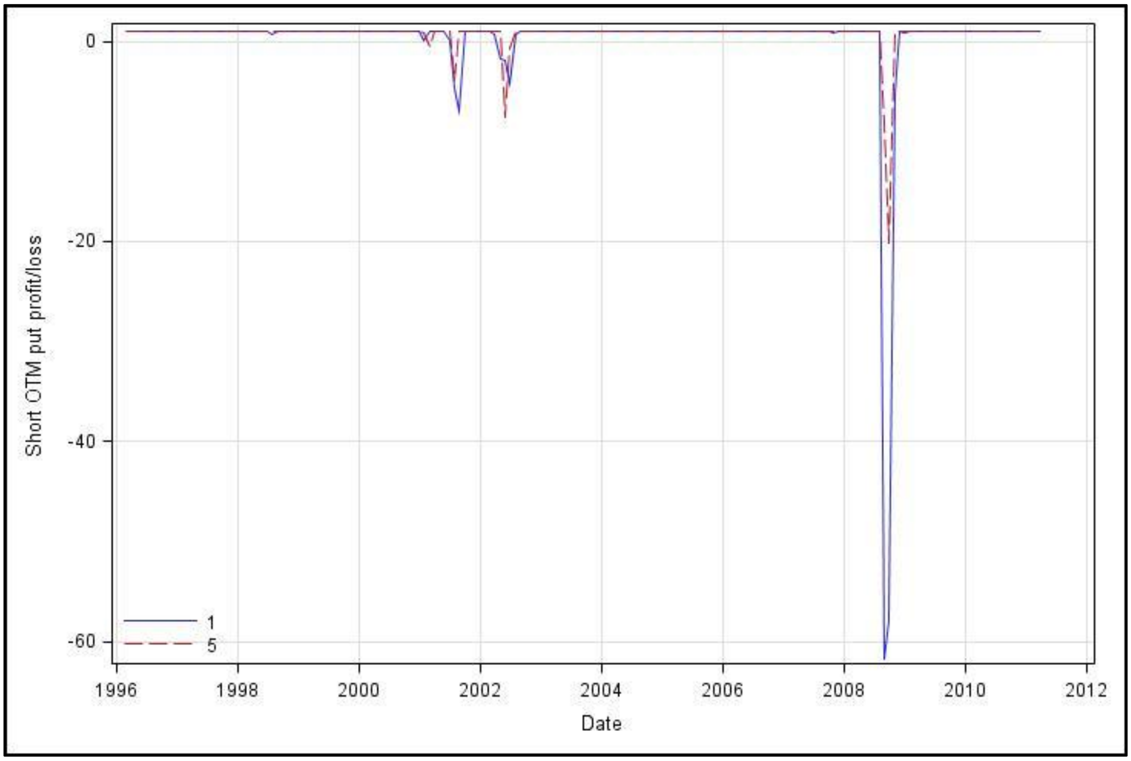

Figure B.10: S&P 500 Put Option Profits and Losses by Fear.
The figure shows profit and losses on short put options on S&P 500 index, from January 1996 to October 2011. Quintile 1, the blue solid line, represents low fear and quintile 5, the dashed red line, represents high fear.

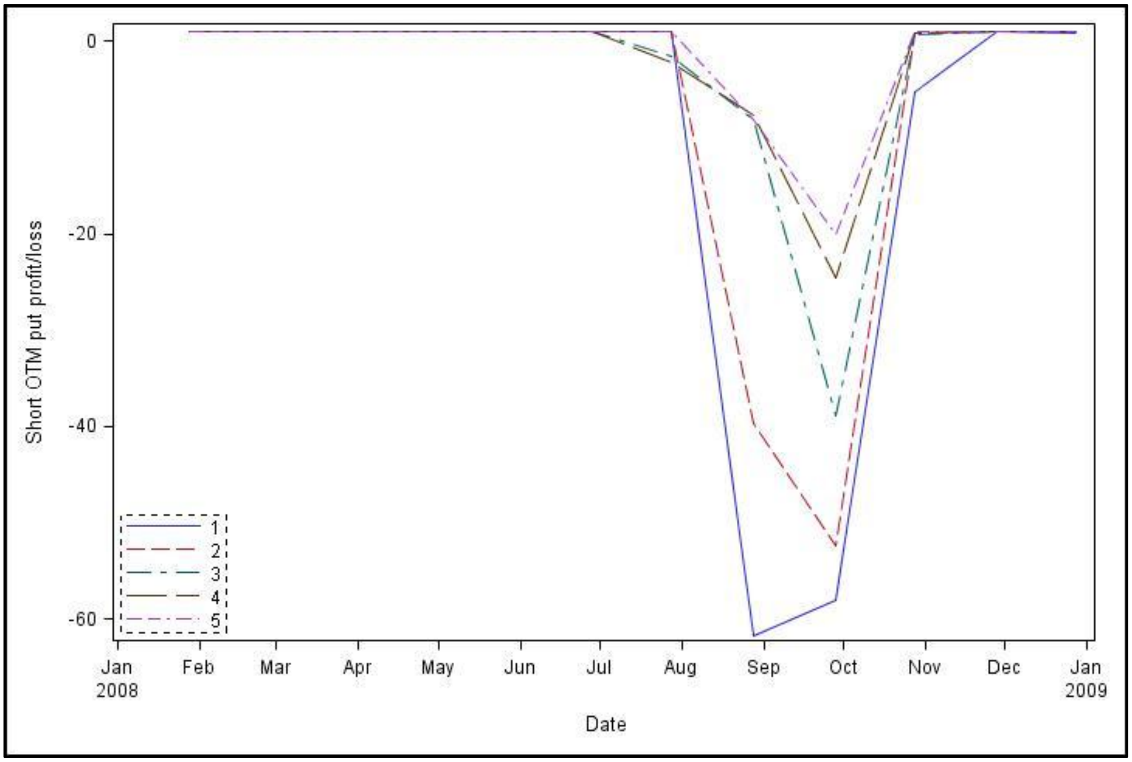

Figure B.11: S&P 500 Put Option Profits and Losses by Fear during the 2008 crisis
The figure shows profit and losses on short put options on S&P 500 index, from January 2008 to January 2009. Quintile 1, the blue solid line, represents low fear and quintile 5, the dashed red line, represents high fear.

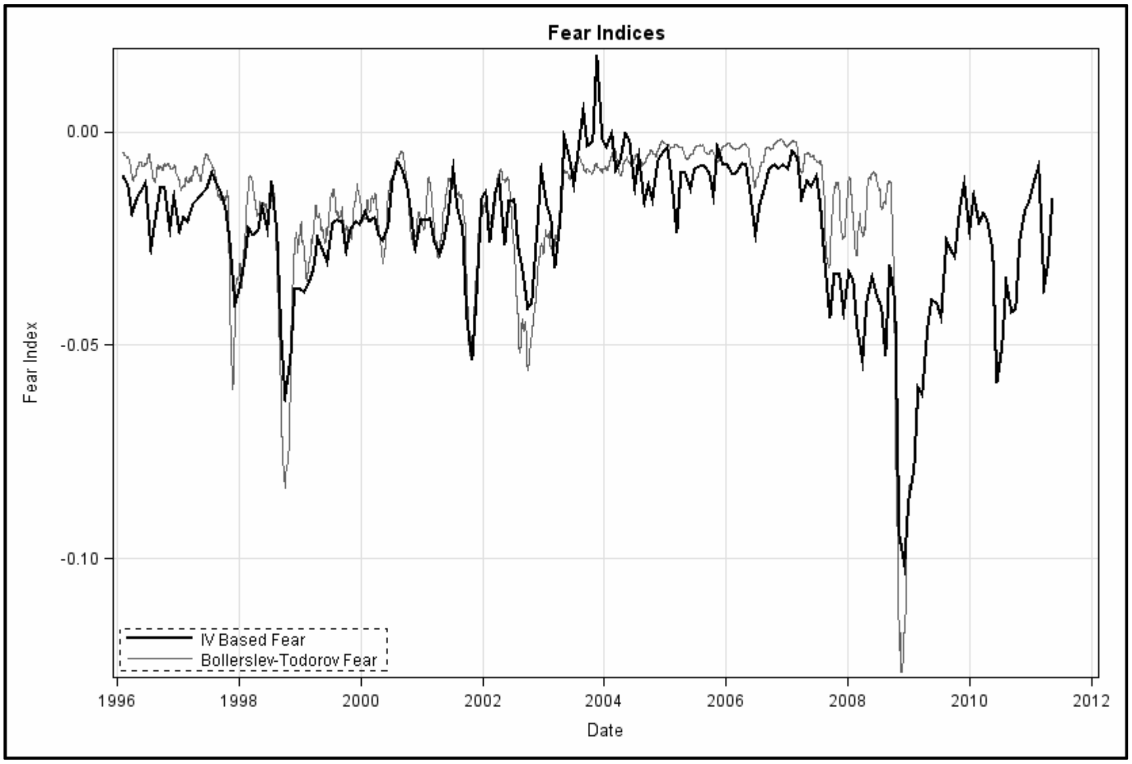

Figure B.12: Alternative Fear Index
The figure shows the estimated value of the fear premium from S&P 500 index options over January 1996 to October 2011. The dark black line is implied volatility based fear measure developed in this study. The lighter black line is the Bollerslev and Todorov (2011) measure of fear. The alternative fear index is constructed using ITM put option implied volatility instead of OTM call option volatility.

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BIOGRAPHICAL INFORMATION

Mishuk Chowdhury was born on September 11, 1983 to Anwarullah Chowdhury and Lucky Nasreen in Dhaka, Bangladesh. The author received his BSc in Computer Science in December of 2003 from Minnesota State University, Mankato. After working full-time in information technology for two years, he joined the MA Economics program at the University of Texas at Arlington, which he finished in 2006. He started pursuing a PhD in Finance at the University of Texas at Arlington in 2009 and Finished in Spring 2012. The author's current research interests include derivatives, asset pricing, risk management and behavioral finance.

In September 2011, Mishuk joined TD Ameritrade Inc. as a risk analyst and continues to work there. He plans to randomly walk between academia and the industry until he finds his place in the world of Finance.