Option Returns and Volatility Mispricing*

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Abstract

We study the cross-section of stock options returns and find an economically important source of mispricing in the options implied volatilities. We sort stocks based on the difference between historical realized volatility and at-the-money implied volatility and construct portfolios of straddles and delta-hedged calls and puts. We find that a zero-cost trading strategy that is long (short) in the portfolio with a large positive (negative) difference in these two volatility measures, produces an economically and statistically significant average monthly return. The results are robust to different market conditions, to stock risk-characteristics, to various industry groupings, to options liquidity characteristics, and are not explained by linear factor models.

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Abstract

We study the cross-section of stock options returns and find an economically important source of mispricing in the options implied volatilities. We sort stocks based on the difference between historical realized volatility and at-the-money implied volatility and construct portfolios of straddles and delta-hedged calls and puts. We find that a zero-cost trading strategy that is long (short) in the portfolio with a large positive (negative) difference in these two volatility measures, produces an economically and statistically significant average monthly return. The results are robust to different market conditions, to stock risk-characteristics, to various industry groupings, to options liquidity characteristics, and are not explained by linear factor models.

1 Introduction

Options give options. They allow investors to have a view about the underlying security price and volatility. A successful option trading strategy must rely on a signal about at least one of those inputs. The most common options trading strategies involve investors' views about the underlying volatility. In other words, behind a volatility trade lies the trader's conviction that the market expectation about future volatility, which is implied by the option price, is somehow not correct. Since all the option pricing models require at least an estimate of the parameters that characterize the probability distribution of future volatility, volatility mis-measurement is the most obvious source of options mispricing.

The literature on measurement and forecasting of realized volatility is indeed quite extensive. The literature is too voluminous to cite here.[1] The interested reader is referred to the recent surveys in Granger and Poon (2003) and Andersen, Bollerslev, Christoffersen, and Diebold (2006). A basic feature of realized volatility that is found in all these studies is mean-reversion: volatility tends to revert to long-run average. This property should be taken into account by options traders and incorporated into their expectations about future volatility. Of course, mean-reversion does not imply that, at any point in time, historical realized volatility is the best estimate of future volatility. However, this feature of volatility does suggest that large deviations of traders expectations of future volatility from historical volatility might be of temporary nature.

We conjecture that a possible way to identify whether an option is mispriced or not is to compare a measure of historical realized volatility (RV) to the market volatility forecast implied by the option price. In the context of Black and Scholes (1973), given the option price it is possible to obtain an estimate of the market's volatility forecast by inverting the pricing formula. The resulting estimate is generally referred to as the implied volatility (IV).[2] We suggest that, even in the absence of a close correspondence between RV and IV, very large deviations between these two volatility estimates are a signal of volatility mispricing. In this paper we empirically investigate this mispricing conjecture by studying the cross-section of U.S. equity options.

[1] For an incomplete list, see Alizadeh, Brandt, and Diebold (2002), Andersen, Bollerslev, Diebold, and Ebens (2001), Bollerslev, Chou, and Kroner (1992), Christensen and Prabhala (1998), French, Schwert, and Stambaugh (1989), and Schwert (1989).

[2] Strictly speaking, IV is only a rough estimate of the market's estimate of future volatility of the underlying asset. Britten-Jones and Neuberger (2000) derive a procedure that gives the correct estimate of the option-implied (i.e. risk-neutral) integrated variance over the life of the option contract when prices are continuous but volatility is stochastic. Jiang and Tian (2005) improve upon this procedure and also show it's validity in a jump-diffusion setting.

In particular, we sort stocks into deciles based on the log difference between their one year historical RV and their at-the-money IV. RV is calculated using the standard deviation of realized daily stock returns over the most recent twelve months. For each stock, we obtain the IV estimate from one month to maturity, at-the-money (ATM) options. In order to partially limit measurement errors we compute the stock's IV by taking the average of the ATM call and put implied-volatilities. This also ensures that we construct a homogenous sample with respect to the options' contract characteristics across stocks, and that we consider the most liquid options contracts for each stock. We form portfolios of options for each of these deciles.

The two most common strategies that are employed to take advantage of volatility mispricing are straddles portfolios and delta-hedging. Accordingly, we calculate equally-weighted monthly portfolio returns of straddles and delta-hedged calls/puts on stocks in each decile. Since both of these strategies have a low delta (first derivative of the option price with respect to the underlying price) they have very little directional exposure to the underlying stocks. To minimize the impact of microstructure effects, we eliminate stale quotes (quotes that have not been revised between two consecutive trading days) and skip a day between the calculation of the signal (difference between RV and IV) and portfolio formation. We find that a zero-cost trading strategy, involving a long position in a portfolio of options with a large positive difference between RV and IV and a short position in a portfolio of options with a large negative difference is very profitable. A long-short portfolio of straddles, for example, has a monthly average return of 21.9% and a Sharpe ratio of 0.626. The returns to straddles portfolios are comparable to those in Coval and Shumway (2001), who report absolute returns of around 3% per week for zero-beta straddles on the S&P 500. Similarly, we find positive returns for high decile portfolios and negative returns for low decile portfolios of delta-hedged calls/puts.

We conduct several tests to understand the nature of these profits. The long-short straddles portfolio has higher average returns when aggregate volatility (proxied by the implied volatility of the S&P 500 index, VIX) is increasing than when it is decreasing. We also find that average returns the long-short straddles portfolio are higher for high beta and small market capitalization stocks. However, the profits due to IV mispricing persist in any beta, size, book-to-market, and momentum portfolios indicating that the "volatility effect" is not subsumed by other effects typical of the cross-section of stock returns. Moreover, the long-short volatility strategy is quite profitable in each industry.

We also examine whether returns to the long-short strategy are related to aggregate risk. We use linear factor models comprising the Fama and French (1993) factors, the

Carhart (1997) momentum factor, and an aggregate volatility factor (return on an ATM straddle on the S&P 500 index) constructed by Coval and Shumway (2001). We find that the return on the long-short straddles portfolio is negatively related to movements in the three Fama and French stock market factors. This suggests that the long-short strategy is attractive because it hedges the sources of aggregate risk that are priced in the stock market. The return on the straddles portfolio is also positively related to the volatility factor. This coupled with the usual assumption of negative risk premium for the volatility factor implies that the straddles strategy is a good hedge for volatility risk as well. Overall, our results indicate that the straddle returns are not explained by the usual risk factors. However, we advise caution in over-interpreting this evidence as we explore only linear factor models for option returns and option payoffs are known to be non-linearly related to payoffs of stocks (see for example Jones (2006)).

There is an extensive literature that documents that transaction costs in the options market are large.[3] We also find that trading frictions reduce the attractiveness of our options portfolios strategy. For instance, the long-short straddles portfolio returns are reduced to 4.1% per month if we consider trading options at an effective spread equal to the quoted spread.[4] Consistent with the notion that liquidity affects the implementation of portfolio strategies, we also find that the profits are higher for illiquid options than for liquid options. To summarize, although liquidity considerations play an important role in the implementation and profitability of option strategies, we find that our mispricing signal leads to economically large profits.

The U.S. market for equity options is active and has grown consistently over the past thirty years. There is evidence that options traders are sophisticated investors. Easley, O'Hara, and Srinivas (1998), Pan and Poteshman (2006), and Xiaoyan, Pan, and Poteshman (2006) show that options' volume contains information about future stock prices. Given the significant size of the market[5] and the quality of option traders, it is useful to consider why options are mispriced. One reason may be that the economic agents do not use all the available information in forming expectations about future stock volatilities. In

[3]See for example Figlewski (1989), George and Longstaff (1993), Gould and Galai (1974), Ho and Macris (1984), Ofek, Richardson, and Whitelaw (2004), Santa-Clara and Saretto (2005), and Swidler and Diltz (1992).

[4]De Fontnouvelle, Fisher, and Harris (2003) and Mayhew (2002) document that typically the ratio of effective to quoted spread is less than 0.5. On the other hand, Battalio, Hatch, and Jennings (2004) study two periods in the later part of the sample, January 200 and June 2002, and find that for a small sample of stocks the ratio of effective spread to quoted spread is around 0.8.

[5]The total volume of the equity options for the year 2004 was worth approximately 220 billion dollars. For comparison, the total volume of the S&P 500 index options was worth about 120 billion dollars (see the Options Clearing Corporation 2004 annual report at `http://www.optionsclearing.com/about/ann_rep/ann_rep_pdf/annual_rep_04.pdf`).

particular, they might ignore the information contained in the cross-sectional distribution of implied volatilities and consider assets individually when forecasting volatility. To test this conjecture, we form alternative real-time estimates of implied volatility using cross-sectional regressions. These predictions have characteristics similar to those of shrinkage estimators even though they are not formally constructed using Bayesian shrinkage techniques. We find that our options portfolios are no longer profitable once we sort stocks based on the difference between RV and our estimate of implied volatility. A second potential reason why the options are incorrectly priced is that the investors overreact to the current information, which is consistent with the findings of Stein (1989) and Poteshman (2001). Stein studies the term structure of the implied volatility of index options and finds that investors overreact to the current information. They ignore the long-run mean reversion in implied volatility and instead overweight the current short-term implied volatility in their estimates of long-term implied volatility. Stein's finding is analogous to our cross-sectional results, where we find that stocks with low (high) current IV are the ones that we predict to have the highest under(over)-pricing in implied volatility. Poteshman (2001) also finds evidence of overreaction in the index options market.

Our paper is related to the small but growing recent literature that analyzes trading in options (as opposed to the voluminous literature on pricing of options). Coval and Shumway (2001) and Bakshi and Kapadia (2003) study trading in index options. Chava and Tookes (2006), Xiaoyan, Pan, and Poteshman (2006) and Xiaoyan (2006) study trading in individual equity options. To the best of our knowledge, we are the first to study the economic impact of volatility mispricing through option trading strategies.

The rest of the paper is organized as follows. The next section discusses the data. Section 3 presents the main results of the paper by studying option portfolio strategies. We conclude in Section 4 with a discussion of the results.

2 Data

The data on options are from the OptionMetrics Ivy DB database. The dataset contains information on the entire U.S. equity option market and includes daily closing bid and ask quotes on American options as well as IVs and deltas for the period from 1996 to 2005. The IVs and deltas are calculated using a binomial tree model using Cox, Ross, and Rubinstein (1979).[6]

[6]Battalio and Schultz (2006) note that, in the Ivy DB database, option and underlying prices are recorded at different times creating problems when an arbitrage relation, the put-call parity, is examined.

We apply a series of data filters to minimize the impact of recording errors. First we eliminate prices that violate arbitrage bounds. For example, we require that the call option price does not fall outside the interval $(Se^{-\tau d} - Ke^{-\tau r}, Se^{-\tau d})$, where S is the value of the underlying asset, K is the option's strike price, d is the dividend yield, r is the risk free rate, and τ is the time to expiration. Second we eliminate all observations for which the ask is lower than the bid, or for which the bid is equal to zero, or for which the spread is lower than the minimum tick size (equal to $0.05 for option trading below $3 and $0.10 in any other cases). Third, to mitigate the impact of stale quotes we eliminate from the sample all the observations for which both the bid and the ask are equal to the previous day quotes.

We construct portfolios of options and their underlying stocks. These portfolios are formed based on information available on the first trading day (usually a Monday) immediately following the expiration Saturday of the month (all the options expire on the Saturday immediately following the third Friday of the expiration month). At any point in time, equity options have traded maturities corresponding to the two near-term months plus two additional months from the January, February or March quarterly cycles. In order to have continuous time series with constant maturity, we consider only those options that mature in the next month. This criterion guarantees that all the option contracts selected have the same maturity of approximately one month. Among these options with one month maturity, we then select the contracts which are closest to ATM. Since strike prices are spaced every $2.5 apart when the strike price is between $5 and $25, $5 apart when the strike price is between $25 and $200, and $10 apart when the strike price is over $200, it is not always possible to select option with exactly the desired moneyness. Options with moneyness lower than 0.95 or higher than 1.05 are eliminated from the sample. We, thus, select an option contract which is close to ATM and expires next month for each stock each month. After expiration the next month, a new option contract with the same characteristics is selected. Our final sample is composed of 120,028 monthly observations. The average moneyness for calls and puts is very close to one. There are 3,885 stocks in the sample for which it is possible to construct at least one IV observation.

We report summary statistics for IV and the annualized RV of the underlying stocks in Table 1. We compute IV as the average of the implied volatilities extracted from the call and the put contracts, selected based on the maturity/moneyness filter following the procedure described above. RV is computed as the standard deviation of daily realized returns of the underlying stock (from the CRSP database) for the period corresponding to

This property of the data is not a problem for us because the tests that we conduct do not require perfectly coordinated trading in the two markets.

the maturity of the option. We first compute the time-series average of these volatilities for each stock and then report the cross-sectional average of these average volatilities. The other statistics are computed in a similar fashion so that the numbers reported in the table are the cross-sectional averages of the time-series statistics, and these can be interpreted as the summary statistics on an "average" stock.

Both IV and RV are close to each other, with values of 58.3% and 60.0% respectively. The overall distribution of RV is, however, more volatile and more positively skewed than that of IV. The average monthly change in both measures of volatility is very close to zero. Changes in IV can be quite drastic and usually correspond to events of critical importance for the survival of a firm. For example, UICI, a health insurance company, has a ΔIV of 86% which corresponds to the release of particularly negative quarter loss for the fourth quarter of 1999. During the month of December, UICI options went from trading at an ATM IV of 31% to an IV of 117%. The stock price lost 56% of its value in the same month. Many of the other large spikes in volatility happen during months of large declines in stock prices. For example, the IV of the stocks in the technology sector jumped over 150% during the burst of the Nasdaq bubble in the spring of 2000. Spikes in individual stock IV also happen on the occasion of earnings announcements (Dubinsky and Johannes (2005)).[7]

Individual equity options share some characteristics with index options, which have been the primary subject of prior research. Figure 1 plots the time series of VIX and the time series of the cross-sectional average IV. Naturally, the level of IV is much higher than that of VIX. Both series have spikes that correspond to important events, such as the Russian crisis of September 1998. The two variables are also highly correlated. The correlation coefficient of the changes in VIX and changes in equal-weighted (value-weighted) average IV is 67% (82%).

However, the two variables differ in an important way – the average stock IV is more persistent than VIX. The autocorrelation coefficient of the average IV is equal to 0.947; the same coefficient is 0.745 for VIX. Another way in which the equity option market differs from the index option market is that the asymmetric volatility effect of Black (1976) is less pronounced for individual equity options. The monthly correlation between the underlying asset return and change in IV is –0.52 for index options and –0.34, on average, for individual stocks (see Dennis, Mayhew, and Stivers (2005) for further discussion of this result).

[7] Approximately 5% of our observations are earnings announcement dates. Removing these observations has no material impact on our results.

3 Option Portfolio Strategies

Option prices are functions of observables (such as underlying price, expiration, moneyness etc.) and unobservables (underlying volatility). Since all option pricing models require at least an estimate of the parameters that characterize the probability distribution of future volatility, volatility mis-measurement is the most obvious source of options mispricing. We sort stocks based on the difference between RV and IV. The motivation for this sorting criterion is based on two empirical regularities. One, volatility is highly persistent (as reported earlier, the autocorrelation coefficient for individual realized stock volatility in our sample is close to 0.95). Second, IV from an option is the markets estimate of future volatility of the underlying asset.[8] Therefore, while there need not exist close correspondence between RV and IV, large deviations between these two volatility estimates are indicative of volatility mispricing of options. For instance, stocks for which IV is much lower than RV are suspected to be underpriced. We explore these conjectures in this section by forming option portfolios.

3.1 Portfolios Formation

We sort stocks into deciles based on the log difference between RV and IV. Decile ten consists of stocks with the highest (positive) difference while decile one consists of stocks with the lowest (negative) difference between these two volatility measures. We give descriptive statistics on these deciles in Table 2. All statistics are first averaged across stocks in each decile to obtain portfolio statistics. The table reports the monthly averages of the continuous time-series of these portfolio statistics. On average, the portfolios contain 102 stock options in each month.

The RV generally increases as one proceeds from decile one to decile ten. Since our stocks are sorted based on the difference between RV an IV, this also implies that IV is higher for lower deciles than for higher deciles. Another illustration of the same phenomenon is by comparing the call/put prices scaled by the stock price. Since all our options are close to ATM, differences in the ratio of option price to underlying price are directly related to the differences in IV – options in decile one are more expensive than those in decile ten.

We also find a positive (negative) difference in decile one (ten) between IV in the portfolio formation month and IV in the previous month. In other words, portfolio formation

[8] See footnote 2.

month represents higher deviations of RV from IV as compared to those in the month before portfolio formation. Finally, we also calculate greeks for the options and find that there is not much variation in these across deciles. For instance, deltas of calls in all deciles are close to 0.53 while the deltas of puts in all deciles are close to –0.47. In unreported results we also find that gammas and vegas are of similar magnitude across deciles.

3.2 Portfolio Returns

We construct time series of call, put, straddle, and delta-hedged call/put returns for each stock in the sample. Recall that we do not include stale quotes in our analysis (we eliminate from the sample all the observations for which both the bid and the ask are equal to the previous day quotes). To further ameliorate microstructure biases, we also initiate option portfolio strategies on the second (Tuesday), as opposed to the first (Monday), trading day after expiration Friday of the month. In other words, we skip a day after the day that we obtain the signal (difference between RV and IV) for sorting stocks. The returns are constructed using, as a reference beginning price, the average of the closing bid and ask quotes and, as the closing price, the terminal payoff of the option depending on the stock price at expiration and the strike price of the option.[9] After expiration the next month, a new option with the same characteristics is selected and a new monthly return is calculated. Prices and returns for the underlying stock are taken from the CRSP database. Equally-weighted monthly returns on calls, puts, and underlying stocks of each portfolio are computed and the procedure is then repeated for every month in the sample.

There are two straightforward ways to exploit volatility mispricing. One is through straddles portfolios and the other is through delta-hedged portfolios. The advantage of delta-hedged portfolios, relative to the straddles portfolio, is potentially lower transaction costs since stock trading is cheaper than options trading. We turn to the issue of execution costs in the Section 3.6. The disadvantage is that straddles returns are more profitable than delta-hedged portfolios because the former benefit from volatility mispricing of two options (call *and* put) while the latter benefit from volatility mispricing of only one option (call *or* put). We form option portfolios following both of these strategies.

The straddle portfolios are formed as a combination of one call and one put. For delta-hedged portfolios, we use the delta (based on the current IV) provided to us by

[9]The options are American. We, however, ignore the possibility of early exercise in our analysis for simplicity. Optimal early exercise decisions would bias our results downwards for the long positions in portfolio and upwards for the short positions in portfolios. The net effect is not clear. See Poteshman and Serbin (2003) for a discussion of early exercise behavior.

the IVY database. To take full advantage of volatility mispricing, a more powerful and profitable approach is to recalculate delta based on an implied volatility estimate. Green and Figlewski (1999) notes that a delta-hedged strategy based on "incorrect" delta entails risk and does not provide a riskless rate of return. We, however, do not attempt to estimate a new delta because we do not have an alternative estimate of implied volatility (only a signal that IV is higher/lower than RV). This means that we are conservative in our construction of delta-hedged portfolios — we earn lower returns and have higher risk.

Table 3 reports the returns on options portfolios. Since the stock returns are on average positive, all the ten call portfolios have positive returns (Panel A), while nine of the ten put portfolios have negative average returns (Panel B).[10] The pattern in the average returns *across* portfolios is in line with the predicted mispricing in volatility. Decile one has lower returns than decile ten. Also the average returns increase monotonically as one goes from decile one to decile ten. For calls (puts) decile one has an average return of 2.8% (–28.1%) while portfolio ten has an average return of 22.1% (0.4%).

The call and put portfolios are, however, characterized by very high volatility that ranges from 53% to 75% per month. We report two measures related to the risk-return trade-off for the portfolios: Sharpe ratio (SR) and certainty equivalent (CE). CE is computed for a long position in the portfolio and is constructed using a power utility with a coefficient of relative risk aversion (γ) equal to three and seven. SR is the most commonly used measure of risk-return trade-off, but CE is potentially a better measure than SR because it takes into account all the moments of the return distribution. Because of the high volatility and the extreme minimum and maximum returns, which imply large high order moments, all call and put portfolios have low SR and negative CE.

The returns to a long-short strategy, that is long in decile ten and short in decile one, are noteworthy. The long-short call and put portfolios have high average return and volatility that are generally lower than that of either portfolio in decile one or ten, leading to large monthly SR equal to 0.377 and 0.780 for calls and puts, respectively. However, the very large minimum return of –245% for calls leads to negative CE for these portfolios.

Straddles portfolio exhibit a striking pattern with returns that go from –12.4% to 9.5% respectively (Panel D). The volatility of the straddles portfolios is also low at between 17% and 26% per month. The long-short straddles strategy has an average return of 21.9% with

[10]The magnitude of returns on options in the middle deciles is also close to the back of the envelope calculations for average expected return of an option. For instance, it can be shown (see Cox and Rubinstein (1985, page 190)) that average return on a call (for a Black-Scholes economy) is equal to $r_S \times \Delta^c \times (S/C)$, where r_S is the return on the stock. For decile five, this translates into an average return of 13% which is close to the sample average return of 12%.

a 20% monthly standard deviation (the minimum monthly return in the sample is –15.1%), leading to a monthly SR of 1.085 and a CE($\gamma = 3$) of 17.3% per month. To put all these numbers in perspective, the value-weighted CRSP portfolio has a monthly SR of 0.111 and a monthly CE of 0.488% ($\gamma = 3$) and –0.022% ($\gamma = 7$) for our sample period. Moreover, the returns to the straddles portfolios are comparable to those in Coval and Shumway (2001, Table III), who report absolute returns of around 3% per week for zero-beta ATM straddles on the S&P 500.[11]

The magnitude of returns for delta-hedged calls (Panel E) and puts (Panel F) is lower than that for straddles, as is to be expected. However, we see that volatility predictability lends itself to positive returns for high decile portfolios and negative returns for low decile portfolios. The long-short 10–1 portfolio returns for delta-hedged calls (puts) are 2.3% (2.6%) with standard deviations of 3.4% (2.4%). The low standard deviation of these portfolios leads to high SRs. For instance, SR for long-short call (put) delta-hedged portfolio is 0.677 (1.089). The absence of huge positive and negative returns also leads to positive CEs. Even with $\gamma = 7$, CE is 1.9% for calls and 2.4% for puts.

Note that these option returns do not appear to be driven by directional exposure to the underlying asset. When underlying stocks are sorted according to the same portfolio classification, the returns of the stock portfolios decline (though not monotonically) as we go from decile one to decile ten (Panel C). However, since the deltas of all long-short options portfolios are close to zero (see Table 2), even with an average stock volatility of 50%, stock returns of –0.5% for the long-short portfolio are unlikely to account for the magnitude of the options portfolios. Finally, note that the results are not driven by microstructure effects. We compute returns from the mid-point prices, which controls for the bid-ask bounce effect of Roll (1984). Moreover we remove stale quotes and skip a day in computing option returns.

We also find that the portfolios constructed by sorting just on the levels of implied volatility do not produce the same patterns in average returns even though the predicted differences in implied volatility are on average inversely related to the level of implied volatility (see Table 2). While it is in general true that options portfolios of stocks with high implied volatility exhibit lower average returns than portfolios of stocks with low implied volatility, average returns for decile portfolios of calls and puts do not exhibit any monotonic pattern and the average return difference between high IV and low IV is economically small

[11] In addition to the simple straddles returns, we also considered zero-delta and zero-beta straddles. Zero-delta straddles were formed using the delta provided by the IVY database, while zero-beta straddles were constructed following the procedure in Coval and Shumway (2001). The returns on these portfolios were very similar to the ones reported in the paper for the plain vanilla straddles.

and not statistically significant. The only notable exception is represented by the long-short straddle portfolio which has an average return of 6.6%.

Altogether the evidence confirms that the ability to identify volatility mispricing leads to high option returns. The long-short straddles and delta-hedged portfolio returns are statistically significant and economically large. Since straddles returns are most clearly related to the source of profitability, we focus on the straddles portfolios in the next two subsections.[12]

3.3 Sub-Sample Returns

We replicate the analysis of Table 3 by dividing the data into two sub-samples. The sub-samples are formed by considering different states of the VIX and the aggregate market return. The states are determined by the sign of the changes in the VIX index and by the sign of the market value-weighted CRSP portfolio returns. Mean returns and t-statistics of the long-short straddles portfolio in these different states are reported in Table 4.

Panel A of Table 4 shows how the portfolio returns differ in periods of increasing and decreasing VIX. The conditional portfolio returns are higher in months in which VIX is increasing. The return difference across these two states of the world increases moving from decile one to decile ten. The average return difference is virtually zero for decile one and 12.7% for portfolio ten. In five of the ten portfolios this difference is significantly greater than zero at the 95% confidence level. The long-short strategy has returns of 28.9% in months of positive changes in VIX and 17.5% in months of negative changes in VIX.

Since options have a positive return when volatility increases, it is not surprising that higher decile portfolios (which are unconditionally underpriced) have greater returns when VIX is increasing. By the same token, the returns on lower decile portfolios (which are unconditionally overpriced) are not significantly negative in states of the world in which VIX is increasing. The flip side of the coin is that lower decile portfolios have significantly negative returns and higher decile portfolios have insignificantly positive returns when VIX is decreasing. The net result, however, is that the difference in returns between these two states is significant only for higher decile portfolios.

In Panel B the sample is divided according to the sign of the market return. Decile one has higher average returns when the market is rising, while the opposite is true for decile

[12]Results for portfolios of calls and puts, and their delta-hedged counterparts, are qualitatively similar and can be obtained from the authors upon request.

ten. The return difference between positive and negative market periods decreases (though not monotonically) as we go from decile one to decile ten. For the long-short portfolio the spread between up and down market is equal to –7.7% and statistically significant. This effect obtains for essentially the same reason as that in Panel A: market returns and VIX are negatively correlated.

Untabulated results for portfolios of calls and puts differ in only one dimension: the call long-short portfolio has a much higher average return (65.0%) when the market is up than when the market is down (–39.2%). The put long-short strategy is more profitable (60.1%) when the market is down than when the market is up (–41.1%). This result, however, is expected because the option prices move in accordance with the direction of the underlying asset. When VIX is considered as the reference state variable, we observe that call portfolio returns are negative when volatility increases while put portfolio returns are negative when volatility decreases. Again, this is to be expected because of the negative correlation between the VIX and the stock market. Market declines correspond to periods of increased volatility making call returns negative and put returns positive. Delta-hedged call and put portfolios behave exactly as straddle portfolios: they are higher when VIX is increasing and when the stock market decreasing, even if differences are not always statistically significant.

We also analyze average portfolio returns obtained by dividing the sample according to different criteria. When the sample is divided in the two subperiods 1996-2000 and 2001-2005 we observe that the strategy average returns are statistically significant in both subsamples, although the average returns are higher for the period 1996–2000. Since the options market is particularly active during months in which the futures options expire ("triple witching friday") we also compute the average return for the strategies in only those particular months and compare these to the returns in other months. We find that there is no statistically meaningful difference in portfolio returns across these two sets of months (the only exception is portfolios of calls and delta-hedged calls - these portfolios have returns that are lower in months of triple witching fridays than other months).

3.4 Stock Characteristics

Since options are derivative securities, it is reasonable to assume that option returns depend on the same sources of risks or characteristics that explain individual stock returns. The absence of a formal theoretical model for the cross-section of option returns further warrants considering stock factors related explanations for option returns. We, therefore, investigate how the long-short straddles portfolio returns are related to equity risk factors and characteristics. We consider two-way independent sorts – one based on volatility difference and the second based on stock characteristics. The characteristics chosen are beta, size, book-to-market and past return. The first three of these are motivated by Fama and French (1992) while the last one is due to evidence of momentum profits by Jegadeesh and Titman (1993).[13] We sort stocks into quintile portfolios, as opposed to decile, to keep the portfolios well populated. Breakpoints for beta, size, book-to-market, and momentum are based on only the stocks in our sample.

Table 5 shows the returns on these double sorted portfolios. Panel A reports the results of double sorts based on volatility forecasts and stock betas. We find that there is no statistically significant difference in returns of high beta stock straddles and those of low beta stock straddles across any volatility quintile. The difference in returns across volatility quintiles, however, is significant across all beta categories. There is also no clear pattern in long-short straddles returns across beta categories.

Panel B shows that stock size does have an impact on straddles returns. The straddles returns are significantly negative for the first volatility quintile for all stocks. However the difference between small and large stocks is not statistically significant. On the other hand, straddle returns for the volatility quintile five are positive for all stocks but the difference between small and large stocks is statistically significant. Comparing across volatility quintiles, the returns to the long-short 5–1 portfolio are significant across all size categories. They are the highest for small stocks at 20.9% and decreases almost monotonically with the increase in market capitalization of the underlying stock.

Panel C shows no clear evidence of relation between stock book-to-market and straddles returns. The difference in returns for volatility quintiles continues to be significant for both value (17.0%) and growth stocks (13.6%). Panel D reports the results of double sorts based on past return performance of stocks and implied volatility forecasts. In all volatility quintiles, straddles on winner stocks have lower returns than straddles on loser stocks, albeit the difference is never statistically significant.

Overall, the magnitude of the long-short straddles portfolio returns seems to be related to the stock characteristics: the average returns are higher for high beta and small market capitalization stocks. However, the profits due to volatility predictability persist in any beta, size, book-to-market, and momentum portfolios indicating that the "volatility effect" is not subsumed by other effects typical of the cross-section of stock returns. The long-

[13] See also Amin, Coval, and Seyhun (2004), who find a relation between index option prices and momentum.

short straddles portfolio has statistically significant average returns that range from 12.1% to 20.9% per month.

Figure 1 shows that the equity option market was particularly active during the years of the "technology bubble." It is, therefore, imperative to establish if the volatility predictability is a phenomenon in only the technology industry. In unreported results, we find this not to be the case. The long-short straddles portfolio is quite profitable in each industry. The highest average return (24.2% per month) is in the finance sector while the lowest return (19.1%) is in the utilities industry. We also check if the distribution of industries is uniform across our deciles and find this to be the case.

We conclude that the option returns covary with the same stock characteristics that are found to be important for stock returns, but this covariance is not enough to explain the portfolio returns based on the volatility mispricing.

3.5 Risk Adjusted Returns

We proceed by examining whether the profitability of the straddles portfolio is related to aggregate risk. We regress the long-short straddles portfolio return on various specifications of a linear pricing model composed by the Fama and French (1993) three factors, the Carhart (1997) momentum factor, and the Coval and Shumway (2001) aggregate volatility factor represented by the excess return on a zero-beta S&P 500 index ATM straddle.[14] Since all the factors are spread traded portfolios, the intercept from these regressions can be interpreted as an alpha. However, option payoffs are non-linearly related to payoffs of stocks. Therefore, a linear factor model is unlikely to characterize the cross-section of option returns. We use a linear model merely to illustrate that the option returns described in this paper are not related to aggregate sources of risk in an obvious way.

Estimated parameters for these factor regressions are reported in Table 6. The first regression shows that the straddles portfolio has a negative loading on the market factor. This is to be expected. Recall that decile ten contains stocks that have lower current implied volatility (and, therefore, lower deltas) than stocks in decile one. Since it can be shown that in a Black and Scholes economy, the beta of an option is related to it's delta (see Cox and Rubinstein (1985, page 190)), the beta of the long-short straddle portfolio is expected to be negative. The second regression shows that the loadings on Fama and

[14]We obtain data on the first four factors from Ken French's website while we construct the straddle factor ourselves following the procedure described in Coval and Shumway (2001). During our sample period, the return on the VIX straddle factor is –10.3% per month.

French factors are negative (although insignificant) too and positive but insignificant for the momentum factor.[15] The straddle portfolio loads positively on the zero-beta straddle portfolio. This is in contrast to the negative loadings of stock returns on the straddle factor as reported in Coval and Shumway (2001) but consistent with the idea that higher volatility is good for option returns. The $\overline{R}^2$'s of all these regressions are relatively large, especially considering that we analyze a long-short portfolio of options.

The returns on the straddles portfolio are negatively related to movements in the three stock market factors. This, therefore, does not suggest that the high positive option returns are explicable in terms of remuneration for risk. To the contrary, the long-short strategy appears to be quite attractive because it also hedges the sources of aggregate risk that are priced in the stock market. The return on the straddles portfolio is also positively related to the aggregate volatility factor. This coupled with the common assumption of a negative volatility risk premium implies that our strategy is also a good hedge for volatility risk. This is also consistent with the evidence presented in Section 3.3, that shows higher long-short straddles returns in periods of increasing market volatility than in periods of decreasing volatility. Overall, our results indicate that the straddle returns reported earlier are not explained by the usual risk factors. However, caution is advised in over interpreting this evidence as we have explored only linear factor models for option returns.[16]

3.6 Trading Execution

There is a large body of literature that documents that transaction costs in the options market are quite large and are in part responsible for some pricing anomalies, such as violations of the put-call parity relation.[17] It is essential to understand to what degree these frictions prevent an investor from exploiting the profits on portfolio strategies studied in this paper. Therefore, in this section we discuss the impact of transaction costs, measured by the bid-ask spread and margin requirements, on the feasibility of the long-short strategy.

[15] As shown in Section 3.4, straddles returns are related to the characteristics of underlying stocks. However, this does not, by itself, imply that the loading of straddles returns on stock factors related to these characteristics will be significant. For instance, even though straddles returns are higher for smaller stocks than they are for larger stocks, this does not imply that the loading of *options* return on SMB *stock* factor should be positive.

[16] We also investigated whether some other sources of risk related to option greeks are related to straddle returns. While these greeks are strictly not priced factors, they can be treated as characteristics that help explain the pattern of returns. In unreported results, we find this not to be the case - the straddle returns loadings on delta, gamma, and vega are insignificantly different from zero.

[17] See for example Figlewski (1989), George and Longstaff (1993), Gould and Galai (1974), Ho and Macris (1984), Ofek, Richardson, and Whitelaw (2004), Santa-Clara and Saretto (2005), and Swidler and Diltz (1992).

We consider the costs associated with executing the trades at prices inside the bid-ask spread. The results reported so far are based on returns computed using the mid-point price as a reference; however it might not be possible to trade at that price in every circumstance. De Fontnouvelle, Fisher, and Harris (2003) and Mayhew (2002) document that the effective spreads for equity options are large in absolute terms but small relative to the quoted spreads. Typically the ratio of effective to quoted spread is less than 0.5. On the other hand, Battalio, Hatch, and Jennings (2004) study a period in the later part of our sample (January 2000 to June 2002) and find that for a small sample of large stocks the ratio of effective spread to quoted spread fluctuates between 0.8 and 1. Since transactions data is not available to us, we consider three effective spread measures equal to 50%, 75%, and 100% of the quoted spread. In other words, we buy (or sell) the option at prices inside the spread. This is done only at the initiation of the portfolio since we terminate the portfolio at the expiration of the option.

In addition, to address the concern that the results might be driven by options that are thinly traded, we repeat the analysis by splitting the sample into different liquidity groups. For each stock we compute the average quoted bid-ask spread and the daily average dollar volume in the previous month of all the option contracts traded on that stock. We then sort stocks based on these characteristics and calculate average returns and t-statistics for the long-short straddles portfolios for these groups of stocks. We report the results of these computations for straddles portfolios in Panel A of Table 7.

Portfolio returns decrease substantially, as expected, after taking transaction costs into account. The average returns of 21.9% to the long-short straddles portfolio are reduced to 8.6% when trading options at effective spreads that are at three quarter of quoted spreads. The liquidity of options also has an impact on returns as returns are higher for thinly traded stocks. Consider, as an illustration, the results for terciles (low, medium and high) obtained by sorting on the average bid-ask spread of options. The returns, computed from mid-points, to the long-short straddles portfolio are 18.0% for stocks with more liquid options (low bid-ask spreads) and 23.9% for stocks with less liquid options (high bid-ask spreads). These returns decline further with transaction costs. If effective spreads are the same as quoted spreads, the returns are still significantly positive at 8.2% for more liquid options and negative (and insignificant) for less liquid options. This pattern arises because, by construction, the impact of transaction costs (as measured by spreads) is higher for the tercile of stocks with less liquid options. The results are qualitatively the same when we sort stocks based on average daily trading volume of their options.

The conjecture that trading costs might be lower for delta-hedged portfolios than for straddles portfolios is investigated in detail in Panel B of Table 7. We consider the transaction costs of trading options only and assume that stocks trades can be executed without frictions. This is, obviously, a simplification (we do not have data on the trading costs of stocks). While this assumption surely biases our returns upwards, we do not believe that it is a serious omission for two reasons. One, stock trading costs are an order of magnitude smaller than those of stocks (Mayhew (2002)). Second, delta-hedged strategies that finish in-the-money require only half the spread to cover the positions at termination.[18] The pattern of higher returns for more liquid options is repeated in this panel. For instance, the returns (calculated using midpoints) on delta-hedged calls increase from 1.1% to 2.9% per month, and the returns on delta-hedged puts increase from 2.3% to 2.6% per month, as one goes from the lowest tercile of most liquid stock options to the highest tercile of least liquid stock options (liquidity as measured by bid-ask spreads). Spreads decrease these returns on the portfolios. For effective spreads equal to the quoted spreads, the delta-hedged calls have statistically insignificant returns of around 0.2% while delta-hedged puts have statistically significant returns of around 0.7%.

Santa-Clara and Saretto (2005) show that margin requirements on short-sale positions can be quite effective at preventing investors to take advantage of large profit opportunities in the S&P 500 options market. However, margins on short positions have a smaller impact on trades that involve options with strike prices close to the money. The short side of the long-short strategy involves options with high current IV. Therefore, these options have high prices and relatively high price-to-underlying ratios. Margin requirements for these options are relatively low and do not materially affect the execution of our strategies.

We conclude that trading costs reduce the profits to our portfolios but do not eliminate them at reasonable estimates of effective spreads.[19] We also find that the profitability of option portfolios is higher for less liquid options, suggesting that predictability of volatility is related to the liquidity of options.

[18]For instance, a delta-hedged call with a delta of 0.9 will require shorting 0.9 shares of stock at initiation and a further shorting of 0.1 shares at expiration if the call finishes in the money (which will deliver one share of stock). Thus, both legs of the transactions in stock are on the same side (sell).

[19]It is useful to note that we skip an additional day in constructing our portfolio strategies. While our motivation for this procedure is to avoid microstructure issues, the unintended consequence of this approach is that our traders trade *only* based on the closing quotes on Tuesday. In actual practice, the option traders would have the whole day to decide when to optimally trade and minimize the market impact costs.

3.7 "Correct" implied volatility

We have shown that portfolios formed by sorting on the difference between historical RV and IV generate substantial profits. A natural question to ask at this stage is what should be the "correct" implied volatility? Although option pricing is beyond the scope of the paper, we can make some progress towards identifying an alternative estimate of implied volatility. To do so, we estimate a cross-sectional regression model for implied volatility, similar in spirit to that of Jegadeesh (1990), who identifies predictable patterns in the cross-section of stock returns. Each month t, we specify the model as follows:

$$\Delta iv_{i,t} = \alpha_t + \beta_{1t}\, iv_{i,t-1} + \beta_{2t}(iv_{i,t-1} - \overline{iv}_{i,t-13:t-2}) + \beta_{3t}(iv_{i,t-1} - rv_{i,t-12:t-1}) + \epsilon_{i,t}\ , \qquad (1)$$

where $iv_{i,t}$ is the natural logarithm of the ATM IV for stock i measured at month t, $\overline{iv}_{i,t-13:t-2}$ is the natural logarithm of the twelve months moving average of IV_i, $rv_{i,t-13:t-2}$ is the natural logarithm of the historical realized volatility (calculated using months $t-12$ to $t-1$) for stock i.

Our model is motivated primarily by the existing empirical evidence of a high degree of mean-reversion in realized volatility, both at the aggregate and individual stock level (see Granger and Poon (2003) and Andersen, Bollerslev, Christoffersen, and Diebold (2006) for comprehensive reviews), and by the evidence in the previous subsections that historical realized volatility is useful for option portfolio strategies. We include twelve months moving averages of $\overline{iv}$ rather than all the lags because the average is a conservative way of using all available information: it involves estimating only one parameter, instead of the twelve parameters corresponding to the twelve lags, and it does not lead to data loss when one of the lags is missing. We predict the change in IV because it is the relevant variable in constructing option strategies. This is equivalent to forecasting the level of IV. We also choose to work in logs, instead of levels, because in this way we avoid the problem of having to truncate the negative fitted values in the prediction of the level of volatility.

We first estimate a Fama and MacBeth (1973) cross-sectional regression at each date t (Monday following the third Friday of the month). We tabulate averages of the cross-sectional estimates and t-statistics adjusted for serial correlation in Panel A of Table 8. We also report the in-sample fit of these regressions measured by the average $\overline{R}_t^2$ of each monthly cross-sectional regression. We find that the change in IV is negatively related to the last period IV, the difference between last period IV and it's twelve-month moving average, and the difference between IV and RV. The average $\overline{R}^2$ is quite large at 18.3%, and at times it is as high as 50%.

Second, we compute a prediction of each stock's implied volatility at the beginning of each month in a real time fashion. We use implied and realized volatility measures available at month t and parameter estimates of equation (1) obtained from month t to obtain a prediction of implied volatility. We label this prediction as $\widehat{\mathrm{IV}}_{i,t}$ and calculate it using the following equation:

$$\Delta\widehat{iv}_{i,t} \;=\; \widehat{\alpha}_t + \widehat{\beta}_{1t}\, iv_{i,t} + \widehat{\beta}_{2t}(iv_{i,t} - \overline{iv}_{i,t-12:t-1}) + \widehat{\beta}_{3t}(iv_{i,t} - rv_{i,t-11:t}). \tag{2}$$

The above equation is a direct analog of equation (1) except that we use the current month's variables on the right hand side of equation (2) in order to use the most recent information for our prediction.

Panel B of Table 8 gives descriptive statistics on portfolios sorted on the difference between RV and IV (the same sorting criterion as in the rest of the paper). We find that $\widehat{\mathrm{IV}}$ is indeed higher (lower) than IV for decile ten (one). The economic implication of this alternative estimate of implied volatility if then pursued by repricing the options involved in the portfolio strategies by plugging the $\widehat{\mathrm{IV}}$ estimate into the Black and Scholes model. We find that our option trading strategy is no longer profitable on these "repriced" options. Returns on long-short portfolios of calls, puts, and straddles are both economically and statistically insignificant.[20]

4 Conclusion

We emphasize that our results do not depend on the validity of the Black and Scholes (1973) model. The correct way to interpret implied volatilities is a representation of option prices (even when they are not based on the Black and Scholes model). One should, thus, view our portfolios sorts as sorts on option prices with decile one (ten) representing over-(under-)priced options. This perspective does not require one to take a stand on the correct option pricing model. The objective of our paper is to document this mispricing and present a strategy to exploit this for economic profits. The issue of finding the correct option price is beyond the scope of this paper (even though we take a tentative stab at this in Section 3.7). We conjecture that the profitability of our portfolios may be higher using alternative estimates (using option prices) of "implied volatility." For instance, Jiang and

[20]Please note that, since the options are American, the Black and Scholes formula is obviously incorrect for pricing. However, our objective in this exercise is not to compute the "true" price of the option, rather it is to show that, on average, superior returns to portfolios are related only to implied volatility (option price) mis-estimation.

Tian (2005) calculate a model-free implied volatility. This is another reparametrization of the option price. Based on our results regarding mispricing of options, we expect that even this measure of implied volatility is biased for the extreme tails of this distribution.

The verdict about what generates this behavior on the part of the economic agents is left for future research. One possibility is that volatility mispricing stems from the fact that economic agents do not use all the available information in forming expectations about future stock volatilities. In particular, they ignore the information contained in the cross-sectional distribution of implied volatilities and consider assets individually when forecasting volatility. This leads them to misestimate the mean reversion parameter in the underlying stochastic volatility and, therefore, incorrectly price the option. The fact that the alternative implied volatility estimate from the cross-sectional model is closer to the true price of the options lends some credence to this possibility.

Although it is not clear whether the failure to incorporate cross-sectional information in volatility forecasts reflects behavioral biases, our evidence is also broadly consistent with the possibility that the investors overreact to current information. Stein (1989) studies the term structure of IV of index options and finds that investors overreact to the current information. They ignore the long run mean reversion in IV and instead overweight the current short-term IV in their estimates of long-term IV. Stein's finding is analogous to our cross-sectional results, where we find that stocks with low (high) current IV are the ones that we predict to have the highest under(over)-pricing in implied volatility. Poteshman (2001) also studies the term structure of various estimates of index IV and arrives at the conclusion that inefficiencies exist.

The evidence presented in this paper suggests that the information contained in historical realized volatility and implied volatility (based on readily available data) allows one to construct profitable trading strategies. In the context of the stock market, post-earnings-announcement drift strategies (Ball and Brown (1968)) and momentum strategies (Jegadeesh and Titman (1993)) have been identified by Fama (1998) as among those posing the most serious challenge to market efficiency. Our paper extends this list by identifying the existence of similar strategies in the hitherto unexplored area of options markets.

References

Alizadeh, Sassan, Michael W. Brandt, and Francis X. Diebold, 2002, Range-based estimation of stochastic volatility models, *Journal of Finance* 57, 1047–1091.

Amin, Kaushik, Joshua D. Coval, and Nejat H. Seyhun, 2004, Index option prices and stock market momentum, *Journal of Business* 77, 835–873.

Andersen, Torben G., Tim Bollerslev, Peter F. Christoffersen, and Francis X. Diebold, 2006, Volatility and Correlation Forecasting, in Elliott Graham, Clive W.J. Granger, and Allan Timmermann, ed.: *Handbook of Economic Forecasting*, vol. 1 . pp. 778–878 (North-Holland: Amsterdam).

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Heiko Ebens, 2001, The distribution of realized stock return volatility, *Journal of Financial Economics* 61, 43–76.

Bakshi, Gurdip, and Nikunj Kapadia, 2003, Delta-hedged gains and the negative market volatility risk premium, *Review of Financial Studies* 16, 527–566.

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159–178.

Battalio, Robert, Brian Hatch, and Robert Jennings, 2004, Toward a national market system for U.S. exchange-listed equity options, *Journal of Finance* 59, 933–962.

Battalio, Robert, and Paul Schultz, 2006, Options and the bubble, *Journal of Finance* 61, 2071–2102.

Black, Fischer, 1976, Studies of stock price volatility changes, *Proceeding of the 1976 meetings of the 1025 American Statistical Association, Business and Economical Statistics Section* pp. 177–181.

——— , and Myron Scholes, 1973, The pricing of options and corporate liabilities, *Journal of Political Economy* 81, 637–654.

Bollerslev, Tim, Ray Y. Chou, and Kenneth F. Kroner, 1992, ARCH modeling in finance: A selective review of the theory and empirical evidence , *Journal of Econometrics* 52, 5–59.

Britten-Jones, Mark, and Anthony Neuberger, 2000, Option prices, implied price processes, and stochastic volatility, *Journal of Finance* 55, 839–866.

Carhart, Mark M., 1997, On persistence in mutual fund perfromance, *Journal of Finance* 52, 57–82.

Chava, Sudheer, and Heather Tookes, 2006, Where (and How) Does News Impact Trading?, Working paper.

Christensen, Bent J., and Nagpurnanand R. Prabhala, 1998, The relation between implied and realized volatility, *Journal of Financial Economics* 50, 125–150.

Coval, Joshua D., and Tyler Shumway, 2001, Expected option returns, *Journal of Finance* 56, 983–1009.

Cox, John, Stephen Ross, and Mark Rubinstein, 1979, Option pricing: A simplified approach, *Journal of Financial Economics* 7, 229–263.

Cox, John C., and Mark Rubinstein, 1985, *Options Markets* (Prentice-Hall: Englewood Cliffs, New Jersey).

De Fontnouvelle, Patrick, Raymond P.H. Fisher, and Jeffrey H. Harris, 2003, The behavior of bid-ask spreads and volume in options markets during the competition for listings in 1999, *Journal of Finance* 58, 2437–2463.

Dennis, Patrick, Stewart Mayhew, and Chris Stivers, 2005, Stock returns, implied volatility innovations, and the asymmetric volatility phenomenon, Working paper, forthcoming in *Journal of Financial and Quantitative Analysis*.

Dubinsky, Andrew, and Michael Johannes, 2005, Earnings announcements and equity options, Working paper.

Easley, David, Maureen O'Hara, and P.S. Srinivas, 1998, Option volume and stock prices: evidence on where informed traders trade, *Journal of Finance* 53, 431–465.

Fama, Eugene F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.

———, and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

———, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: empirical tests, *Journal of Political Economy* 81, 607–636.

Figlewski, Stephen, 1989, Options arbitrage in imperfect markets, *Journal of Finance* 44, 1289–1311.

French, Kenneth R., William G. Schwert, and Robert F. Stambaugh, 1989, Expected stock returns and volatility., *Journal of Financial Economics* 19, 3–29.

George, Thomas J., and Francis A. Longstaff, 1993, Bid-ask spreads and trading activity in the S&P 100 index option market, *Journal of Financial and Quantitative Analysis* 28, 381–397.

Gould, John P., and Dan Galai, 1974, Transactions costs and the relationship between put and call prices, *Journal of Financial Economics* 1, 105–129.

Granger, Clive W.J., and Ser-Huang Poon, 2003, Forecasting volatility in financial markets: a review, *Journal of Economic Literature* 41, 478–539.

Green, Clifton T., and Stephen Figlewski, 1999, Market risk and model risk for financial institution writing options, *Journal of Finance* 54, 1465–1499.

Ho, Thomas S.Y., and Richard G. Macris, 1984, Dealer bid-ask quotes and transaction prices: an empirical study of some AMEX options, *Journal of Finance* 39, 23–45.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.

——— , and Sheridan Titman, 1993, Returns to buying winners and selling losers: implications for stock market efficiency, *Journal of Finance* 47, 65–91.

Jiang, George J., and Yisong S. Tian, 2005, The model-free implied volatility and its information content, *Review of Financial Studies* 18, 1305–1342.

Jones, Christopher S., 2006, A nonlinear factor analysis of S&P 500 index options returns, *Journal of Finance* 61, 2325–2363.

Mayhew, Stewart, 2002, Competition, market structure, and bid-ask spreads in stock option markets, *Journal of Finance* 57, 931–958.

Ofek, Eli, Matthew Richardson, and Robert F. Whitelaw, 2004, Limited arbitrage and short sales restrictions: evidence from the options market, *Journal of Financial Economics* 74, 305–342.

Pan, Jun, and Allen M. Poteshman, 2006, The information in option volume for future stock prices, *Review of Financial Studies* 19, 871–908.

Poteshman, Allen M., 2001, Underreaction, overreaction, and increasing misreaction to information in the options market, *Journal of Finance* 56, 851–876.

——— , and Vitaly Serbin, 2003, Clearly irrational financial market behavior: Evidence from the early exercise of exchange traded stock options, *Journal of Finance* 58, 37–70.

Roll, Richard, 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, *Journal of Finance* 4, 1127–1139.

Santa-Clara, Pedro, and Alessio Saretto, 2005, Option strategies: Good deals and margin calls, UCLA working paper.

Schwert, William G., 1989, Why does stock market volatility change over time?, *Journal of Finance* 44, 1115 1153.

Stein, Jeremy, 1989, Overreactions in the options market, *Journal of Finance* 44, 1011–1023.

Swidler, Steve, and David J. Diltz, 1992, Implied volatilities and transaction costs, *Journal of Financial and Quantitative Analysis* 27, 437–447.

Xiaoyan, Sophie Ni, 2006, Stock option return: a puzzle, Working Paper.

——— , Jun Pan, and Allen M. Poteshman, 2006, Volatility Information Trading in the Option Market, Working Paper.

Figure 1: VIX and IV

We select one call and one put for each stock in each month of the sample period. All options have expirations of one month and moneyness close to one. The IV for each stock is the average of the IV of the selected call and put. All options are American. The figure plots the time-series of VIX and the time-series of the average IV. The sample period is January 1996 to December 2005.

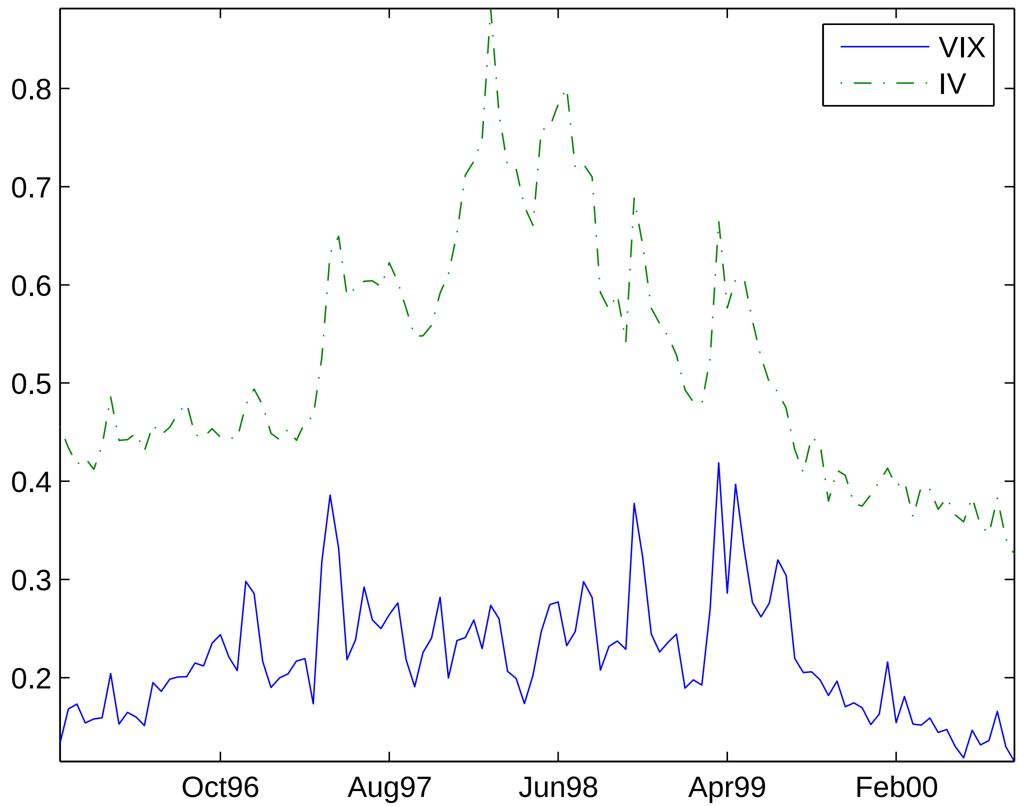

Table 1: Summary Statistics

This table reports summary statistics of the options used in this paper. We select one call and one put for each stock in each month of the sample period. All options have expirations of one month and moneyness close to one. We first compute the time-series average of these volatilities for each stock and then report the cross-sectional average of these average volatilities. The other statistics are computed in a similar fashion. We report statistics for the level and change of the ATM implied volatilities (IV), the smiles, and the level and change of the realized volatilities (RV). The IV for each stock is the average of the IV of the selected call and put. The volatilities are in annualized basis. The sample period is 1996 to 2005.

	Mean	Median	StDev	Min	Max	Skew	Kurt
IV	0.583	0.565	0.133	0.401	0.882	0.570	3.116
Δ IV	-0.003	-0.007	0.159	-0.288	0.307	0.160	3.193
RV	0.600	0.591	0.111	0.445	0.796	0.235	2.365
Δ RV	-0.002	-0.002	0.026	-0.052	0.049	0.045	4.567

Table 2: Descriptive Statistics of Portfolios Sorted on the Difference Between Historical Realized Volatility and Implied Volatility

We select one call and one put for each stock in each month of the sample period. All options have expirations of one month and moneyness close to one. Stocks are sorted into deciles based on the difference between historical RV and current IV. IV is computed as the average of the implied volatilities extracted from the selected call and the put while RV is computed using last year's daily stock returns. Decile ten consists of stocks with the highest (positive) difference while decile one consists of stocks predicted to have the lowest (negative) difference between these two volatility measures. All statistics are first averaged across stocks in each decile (the time-series average number of stocks in each decile is 102). The table reports the monthly averages of these cross-sectional averages for each reported number. Numbers in parenthesis are t-statistics. The sample period is 1996 to 2005.

Decile	1	2	3	4	5	6	7	8	9	10
$\mathrm{RV}_t - \mathrm{IV}_t$	-0.160	-0.081	-0.048	-0.024	-0.003	0.018	0.040	0.066	0.104	0.212
RV_t	0.403	0.423	0.441	0.450	0.468	0.489	0.510	0.534	0.574	0.688
IV_t	0.563	0.503	0.489	0.474	0.470	0.472	0.470	0.467	0.470	0.476
IV_{t-1}	0.498	0.522	0.513	0.516	0.505	0.510	0.499	0.510	0.517	0.500
$(\mathrm{C/S})_t$	0.064	0.058	0.056	0.054	0.053	0.053	0.053	0.052	0.053	0.053
$(\mathrm{P/S})_t$	0.063	0.055	0.054	0.054	0.053	0.053	0.053	0.054	0.054	0.057
Δ_t^C	0.553	0.547	0.540	0.539	0.532	0.530	0.527	0.524	0.522	0.521
Δ_t^P	-0.451	-0.458	-0.464	-0.466	-0.471	-0.475	-0.478	-0.481	-0.482	-0.485

Table 3: Portfolio Returns for Deciles Sorted on Difference Between Historical Realized Volatility and Implied Volatility

Stocks are sorted into deciles based on the same procedure as in Table 2. Decile ten consists of stocks with the highest (positive) difference while decile one consists of stocks predicted to have the lowest (negative) difference between RV and IV. The returns on options are constructed using, as a reference beginning price, the average of the closing bid and ask quotes and, as the closing price, the terminal payoff of the option depending on the stock price and the strike price of the option. . The delta-hedged portfolios are constructed by buying (or shorting) appropriate shares of underlying stock. The hedge ratio for these portfolios is calculated using the current IV estimate. The monthly returns on options are averaged across all the stocks in the volatility decile. The table then reports the descriptives on this continuous time-series of monthly returns. Specifically, we report the mean, standard deviation, minimum, maximum, Sharpe ratio (SR), and the certainty equivalent (CE). CE is computed from a utility function with constant relative risk-aversion parameters of three and seven. The sample period is 1996 to 2005.

Decile	1	2	3	4	5	6	7	8	9	10	10–1
					Panel A: Call Returns						
mean	0.028	0.049	0.086	0.090	0.120	0.128	0.130	0.121	0.133	0.221	0.193
std	0.588	0.583	0.588	0.600	0.624	0.647	0.653	0.665	0.664	0.740	0.512
min	-0.920	-0.921	-0.905	-0.994	-0.930	-0.922	-0.967	-0.962	-0.979	-0.967	-2.447
max	2.286	2.270	1.984	1.648	2.064	2.363	2.227	2.067	2.012	2.772	2.043
SR	0.042	0.078	0.142	0.146	0.188	0.194	0.194	0.178	0.196	0.294	0.377
CE ($\gamma = 3$)	-0.542	-0.544	-0.545	-0.934	-0.610	-0.540	-0.712	-0.738	-0.796	-0.728	-0.088
CE ($\gamma = 7$)	-0.825	-0.830	-0.812	-0.986	-0.856	-0.831	-0.926	-0.924	-0.955	-0.927	-0.496
					Panel B: Put Returns						
mean	-0.281	-0.219	-0.213	-0.179	-0.162	-0.149	-0.099	-0.083	-0.080	0.004	0.284
std	0.531	0.597	0.585	0.643	0.632	0.663	0.679	0.655	0.670	0.751	0.364
min	-0.923	-0.897	-0.896	-0.900	-0.865	-0.847	-0.906	-0.919	-0.946	-0.903	-0.302
max	2.380	2.653	2.401	3.471	3.048	3.261	3.183	2.823	2.841	3.614	1.426
SR	-0.535	-0.372	-0.369	-0.283	-0.261	-0.230	-0.150	-0.131	-0.124	0.001	0.780
CE ($\gamma = 3$)	-0.679	-0.642	-0.655	-0.609	-0.567	-0.551	-0.614	-0.569	-0.651	-0.558	0.157
CE ($\gamma = 7$)	-0.842	-0.803	-0.811	-0.789	-0.741	-0.710	-0.808	-0.822	-0.880	-0.790	0.038

Decile	1	2	3	4	5	6	7	8	9	10	10–1
Panel C: Stock returns											
mean	0.014	0.012	0.014	0.014	0.013	0.012	0.011	0.009	0.011	0.009	-0.005
std	0.060	0.059	0.060	0.059	0.063	0.065	0.066	0.068	0.069	0.078	0.044
min	-0.171	-0.186	-0.194	-0.217	-0.224	-0.225	-0.232	-0.251	-0.226	-0.232	-0.174
max	0.152	0.130	0.150	0.169	0.156	0.211	0.194	0.171	0.229	0.323	0.215
SR	0.185	0.153	0.189	0.178	0.166	0.142	0.123	0.089	0.111	0.074	-0.123
CE ($\gamma = 3$)	0.009	0.007	0.009	0.008	0.007	0.006	0.004	0.002	0.003	-0.001	-0.008
CE ($\gamma = 7$)	0.001	-0.001	0.000	-0.001	-0.003	-0.005	-0.007	-0.010	-0.008	-0.014	-0.013
Panel D: Straddle Returns											
mean	-0.124	-0.073	-0.054	-0.042	-0.017	-0.016	-0.002	0.016	0.028	0.095	0.219
std	0.166	0.183	0.186	0.201	0.209	0.235	0.214	0.225	0.220	0.258	0.202
min	-0.404	-0.412	-0.362	-0.344	-0.375	-0.375	-0.407	-0.439	-0.334	-0.306	-0.151
max	0.578	0.850	0.746	1.026	0.965	1.301	1.311	1.134	1.083	1.302	1.009
SR	-0.766	-0.413	-0.307	-0.223	-0.094	-0.081	-0.022	0.056	0.112	0.357	1.085
CE ($\gamma = 3$)	-0.163	-0.116	-0.099	-0.087	-0.068	-0.074	-0.051	-0.042	-0.025	0.028	0.173
CE ($\gamma = 7$)	-0.201	-0.166	-0.145	-0.128	-0.116	-0.129	-0.108	-0.109	-0.080	-0.037	0.119
Panel E: Delta-Hedged Call Returns											
mean	-0.014	-0.009	-0.007	-0.005	-0.003	-0.003	0.001	0.002	0.002	0.009	0.023
std	0.027	0.023	0.023	0.024	0.025	0.027	0.028	0.026	0.026	0.031	0.034
min	-0.060	-0.063	-0.056	-0.061	-0.044	-0.053	-0.046	-0.053	-0.056	-0.041	-0.129
max	0.115	0.098	0.102	0.119	0.126	0.146	0.141	0.147	0.137	0.147	0.157
SR	-0.620	-0.526	-0.440	-0.349	-0.235	-0.206	-0.071	-0.056	-0.022	0.205	0.677
CE ($\gamma = 3$)	-0.015	-0.010	-0.008	-0.006	-0.004	-0.004	-0.000	0.001	0.001	0.008	0.021
CE ($\gamma = 7$)	-0.016	-0.011	-0.009	-0.007	-0.005	-0.005	-0.001	-0.001	0.000	0.006	0.019
Panel F: Delta-Hedged Put Returns											
mean	-0.017	-0.009	-0.007	-0.005	-0.001	-0.001	0.001	0.002	0.003	0.009	0.026
std	0.021	0.020	0.020	0.021	0.020	0.023	0.021	0.021	0.021	0.027	0.024
min	-0.103	-0.074	-0.075	-0.053	-0.035	-0.068	-0.046	-0.051	-0.036	-0.049	-0.012
max	0.088	0.089	0.085	0.119	0.116	0.118	0.106	0.113	0.095	0.141	0.142
SR	-0.922	-0.627	-0.472	-0.364	-0.205	-0.189	-0.104	-0.059	-0.001	0.236	1.089
CE ($\gamma = 3$)	-0.017	-0.010	-0.007	-0.005	-0.002	-0.002	0.000	0.001	0.002	0.008	0.025
CE ($\gamma = 7$)	-0.018	-0.011	-0.008	-0.006	-0.002	-0.003	-0.001	0.000	0.002	0.007	0.024

Table 4: Straddles Portfolio Returns in Subsamples

Stocks are sorted into deciles based as in Table 2. Decile ten consists of stocks with the highest (positive) difference while decile one consists of stocks predicted to have the lowest (negative) difference between RV and IV. Returns on options are constructed based on the same procedure as in Table 3. The monthly returns on options are averaged across all the stocks in the volatility decile. The table then reports the descriptives on this continuous time-series of monthly returns. We separate the sample period into two states based on the market returns in Panel A and the market volatility in Panel B. The market return is proxied by the value-weighted return on CRSP market portfolio while market volatility is measured by VIX. The first row gives the average return while the second row gives the t-statistics of the return in parenthesis. The sample period is 1996 to 2005.

					Volatility Decile					
1	2	3	4	5	6	7	8	9	10	10–1
					Panel A: Based on market volatility					
					Up volatility					
-0.114	-0.041	-0.029	0.003	0.017	0.047	0.084	0.085	0.090	0.175	0.289
(-4.05)	(-1.23)	(-0.88)	(0.09)	(0.46)	(1.04)	(2.06)	(2.02)	(2.25)	(3.98)	(10.40)
					Down volatility					
-0.127	-0.092	-0.066	-0.064	-0.033	-0.049	-0.052	-0.024	-0.008	0.048	0.175
(-7.09)	(-4.98)	(-3.44)	(-3.48)	(-1.57)	(-2.31)	(-2.83)	(-1.15)	(-0.40)	(1.82)	(7.60)
					Up − Down					
0.013	0.051	0.036	0.068	0.051	0.096	0.136	0.109	0.098	0.127	0.114
(0.40)	(1.35)	(0.94)	(1.59)	(1.18)	(1.93)	(3.04)	(2.32)	(2.17)	(2.48)	(3.16)
					Panel B: Based on market returns					
					Up market					
-0.109	-0.072	-0.047	-0.043	-0.015	-0.022	-0.016	-0.003	0.010	0.079	0.188
(-6.06)	(-3.84)	(-2.48)	(-2.30)	(-0.70)	(-1.00)	(-0.85)	(-0.13)	(0.50)	(2.99)	(7.88)
					Down market					
-0.147	-0.073	-0.065	-0.041	-0.020	-0.008	0.019	0.042	0.052	0.118	0.265
(-5.52)	(-2.37)	(-2.05)	(-1.12)	(-0.55)	(-0.19)	(0.50)	(1.04)	(1.34)	(2.72)	(9.27)
					Up − Down					
0.038	0.002	0.018	-0.002	0.005	-0.014	-0.036	-0.045	-0.042	-0.039	-0.077
(1.17)	(0.04)	(0.49)	(-0.05)	(0.11)	(-0.29)	(-0.83)	(-0.99)	(-0.95)	(-0.78)	(-2.07)

Table 5: Straddles Returns by Volatility Forecast and Stock Characteristics

We sort stocks independently into quintiles based on the difference between the historical RV and the current IV (as in Table 2) and into quintiles based on stock characteristics. For volatility sorts, quintile five consists of stocks with the highest (positive) difference while quintile one consists of stocks predicted to have the lowest (negative) difference between these two volatility measures. We consider four stock characteristics, namely beta (Panel A), market size (Panel B), book-to-market ratio (Panel C), and momentum (Panel D). Breakpoints for these stock characteristics are calculated each month based only on stocks in our sample. Returns on options are constructed based on the same procedure as in Table 3. The monthly returns on options are averaged across all the stocks in each of these 5×5 sub-groups. The table then reports the average return and the associated t-statistic of this continuous time-series of monthly returns on the straddles in each of the sub-groups. The sample period is 1996 to 2005.

	Volatility Quintile						Volatility Quintile					
	1	2	3	4	5	5–1	1	2	3	4	5	5–1
Panel A: Based on stock beta												
	Mean						t-statistic					
L=1	-0.101	-0.040	-0.046	-0.031	0.031	0.132	-4.93	-1.67	-2.03	-1.04	1.17	4.99
2	-0.095	-0.064	-0.019	0.002	0.035	0.130	-4.77	-2.82	-0.82	0.08	1.31	5.59
3	-0.087	-0.021	-0.010	0.015	0.080	0.167	-4.15	-0.91	-0.34	0.56	2.85	7.23
4	-0.100	-0.037	-0.006	0.008	0.049	0.149	-4.91	-1.67	-0.25	0.29	1.92	6.51
H=5	-0.100	-0.039	-0.023	0.015	0.068	0.169	-4.14	-1.58	-0.82	0.58	2.55	5.78
H–L	0.001	0.001	0.023	0.045	0.037		0.03	0.04	0.72	1.45	1.32	
Panel B: Based on stock market capitalization												
	Mean						t-statistic					
S=1	-0.126	-0.063	-0.023	0.022	0.083	0.209	-7.57	-3.40	-1.10	0.98	3.67	11.89
2	-0.078	-0.030	0.003	0.027	0.106	0.184	-4.22	-1.58	0.13	1.26	4.18	8.01
3	-0.108	-0.052	-0.009	0.026	0.069	0.176	-6.04	-2.53	-0.40	1.08	2.84	8.34
4	-0.067	-0.039	0.001	-0.005	0.054	0.121	-3.29	-1.91	0.04	-0.21	2.12	5.77
B=5	-0.118	-0.044	-0.033	-0.010	0.011	0.129	-5.92	-1.87	-1.27	-0.36	0.35	5.13
S–B	-0.008	-0.019	0.010	0.032	0.072		-0.42	-0.85	0.41	1.29	2.84	

Panel C: Based on stock book-to-market

	Volatility Quintile						Volatility Quintile					
	1	2	3	4	5	5–1	1	2	3	4	5	5–1
	Mean						t-statistic					
G=1	-0.090	-0.030	-0.007	0.016	0.046	0.136	-5.25	-1.50	-0.29	0.66	1.93	6.90
2	-0.102	-0.060	-0.017	0.014	0.055	0.157	-5.57	-2.95	-0.78	0.69	2.38	8.71
3	-0.107	-0.038	-0.004	0.028	0.068	0.175	-5.61	-1.77	-0.15	1.14	2.53	8.14
4	-0.089	-0.049	-0.022	-0.007	0.079	0.168	-4.39	-2.23	-0.96	-0.28	2.73	6.59
V=5	-0.079	-0.030	-0.004	-0.003	0.092	0.170	-3.40	-1.35	-0.13	-0.09	2.99	5.59
V–G	0.012	0.001	0.003	-0.019	0.046		0.52	0.03	0.09	-0.67	1.53	

Panel D: Based on stock momentum

	Volatility Quintile						Volatility Quintile					
	1	2	3	4	5	5–1	1	2	3	4	5	5–1
	Mean						t-statistic					
L=1	-0.077	-0.041	-0.002	0.024	0.089	0.165	-3.85	-2.03	-0.11	1.10	3.64	7.40
2	-0.107	-0.044	-0.012	-0.003	0.069	0.176	-5.46	-2.11	-0.48	-0.13	2.92	7.73
3	-0.110	-0.047	-0.020	0.008	0.047	0.157	-6.31	-2.29	-0.75	0.33	1.79	7.27
4	-0.095	-0.043	-0.026	0.005	0.052	0.146	-5.24	-2.08	-1.12	0.24	1.95	6.58
W=5	-0.086	-0.049	-0.007	0.015	0.059	0.145	-4.54	-2.33	-0.31	0.60	2.34	6.85
W–L	-0.009	-0.008	-0.005	-0.009	-0.030		-0.46	-0.36	-0.22	-0.34	-1.45	

Table 6: Risk-Adjusted Straddles Returns

Stocks are sorted into deciles based as in Table 2. Decile ten consists of stocks with the highest (positive) difference while decile one consists of stocks predicted to have the lowest (negative) difference between RV and IV. Returns on options are constructed based on the same procedure as in Table 3. The monthly returns on options are averaged across all the stocks in the volatility decile. We then regress the 10–1 straddles portfolio returns on risk factors. We consider risk factors from the Fama and French (1993) three-factor model (MKT-Rf, SMB, and HML), the Carhart (1997) momentum factor (MOM), and the Coval and Shumway (2001) excess zero-beta VIX straddle factor (ZBSTRAD-Rf). The first row gives the coefficient while the second row gives the *t*-statistics in parenthesis. The sample period is 1996 to 2005.

	(1)	(2)	(3)	(4)	(5)
Alpha	0.225	0.232	0.230	0.234	0.238
	(11.82)	(12.24)	(11.23)	(12.38)	(12.67)
MKT-Rf	-0.887	-1.172		-0.733	-0.982
	(-1.48)	(-1.81)		(-1.34)	(-1.69)
SMB		-0.887			-0.671
		(-1.21)			(-0.94)
HML		-1.279			-0.957
		(-1.84)			(-1.53)
MOM		0.252			0.115
		(0.51)			(0.24)
ZB-STRAD-Rf			0.093	0.085	0.075
			(3.39)	(3.13)	(3.05)
$\overline{R}^2$	0.042	0.066	0.094	0.121	0.122

Table 7: Impact of Liquidity and Transaction Costs

We sort stocks independently into deciles based on the difference between the historical RV and the current IV (as in Table 2) and into terciles based on stock options liquidity characteristics. For volatility sorts, decile ten consists of stocks with the highest (positive) difference while decile one consists of stocks predicted to have the lowest (negative) difference between these two volatility measures. For stock options liquidity sorts, we consider terciles based on the average quoted bid-ask spread of all the options series traded in the previous month, as well as terciles based on daily average dollar volume of all the options series traded in the previous month. The returns on options are computed from the mid-point opening price (MidP) and from the effective bid-ask spread (ESPR), estimated to be equal to 50%, 75%, and 100% of the quoted spread (QSPR). The closing price of options is equal to the terminal payoff of the option depending on the stock price and the strike price of the option. The delta-hedged portfolios are constructed by buying (or shorting) appropriate shares of underlying stock. The hedge ratio for these portfolios is calculated using the current IV estimate. The monthly returns on options (or delta-hedged portfolios) are averaged across all the stocks in any particular sub-group. Panel A reports returns on long-short 10–1 straddles portfolio while Panel B reports returns on long-short 10–1 delta-hedged calls/puts. First row shows the average return while the second row shows the associated t-statistic (in parenthesis) of this continuous time-series of monthly returns in each of the three stock options' liquidity sub-groups. The sample period is 1996 to 2005.

Panel A: Returns on 10–1 straddles portfolios

		ESPR/QSPR		
	MidP	50%	75%	100%
All	0.219	0.130	0.086	0.041
	(11.83)	(7.20)	(4.78)	(2.26)
Based on average bid-ask spread of options				
Low	0.180	0.127	0.103	0.082
	(6.68)	(4.88)	(4.01)	(3.16)
Medium	0.220	0.135	0.096	0.059
	(8.65)	(5.48)	(3.93)	(2.39)
High	0.239	0.113	0.053	-0.008
	(10.46)	(5.11)	(2.42)	(-0.35)
Based on average trading volume of options				
Low	0.233	0.124	0.070	0.015
	(10.25)	(5.63)	(3.19)	(0.66)
Medium	0.215	0.133	0.093	0.052
	(9.02)	(5.73)	(4.02)	(2.25)
High	0.177	0.119	0.090	0.061
	(6.32)	(4.33)	(3.30)	(2.25)

Panel B: Returns on 10–1 Delta-Hedged portfolios								
	Delta-Hedged Call Returns				Delta-Hedged Put Returns			
		ESPR/QSPR				ESPR/QSPR		
	MidP	50%	75%	100%	MidP	50%	75%	100%
All	0.023	0.013	0.007	0.002	0.026	0.016	0.012	0.007
	(7.38)	(4.12)	(2.46)	(0.77)	(11.88)	(7.59)	(5.37)	(3.12)
Based on average bid-ask spread of options								
Low	0.011	0.005	0.003	-0.000	0.023	0.017	0.015	0.012
	(1.59)	(0.79)	(0.39)	(-0.02)	(6.12)	(4.66)	(3.97)	(3.31)
Medium	0.026	0.016	0.012	0.007	0.027	0.017	0.013	0.009
	(7.02)	(4.48)	(3.23)	(1.98)	(9.19)	(6.08)	(4.58)	(3.11)
High	0.029	0.015	0.008	0.001	0.026	0.013	0.006	-0.000
	(10.25)	(5.39)	(2.94)	(0.42)	(11.43)	(5.66)	(2.81)	(-0.08)
Based on average trading volume of stock options								
Low	0.028	0.015	0.009	0.002	0.026	0.014	0.008	0.002
	(9.87)	(5.49)	(3.22)	(0.90)	(11.03)	(6.14)	(3.59)	(1.00)
Medium	0.030	0.021	0.016	0.011	0.027	0.018	0.013	0.009
	(9.07)	(6.32)	(4.88)	(3.40)	(9.53)	(6.44)	(4.84)	(3.20)
High	0.007	0.001	-0.002	-0.005	0.022	0.015	0.012	0.009
	(0.88)	(0.09)	(-0.32)	(-0.73)	(5.85)	(4.24)	(3.41)	(2.58)

Table 8: Cross-sectional model for predicting implied volatility

We select one call and one put for each stock in each month of the sample period. All options have expirations of one month and moneyness close to one. Panel A reports the time-series averages of the following Fama and MacBeth (1973) regression (t-statistics adjusted for serial correlation in parenthesis below the coefficient):

$$\Delta iv_{i,t} = \alpha_t + \beta_{1t}\, iv_{i,t-1} + \beta_{2t}(iv_{i,t-1} - \overline{iv}_{i,t-12:t-1}) + \beta_{3t}(iv_{i,t-1} - rv_{i,t-12:t-1}) + \epsilon_{i,t}\ ,$$

where IV is the implied volatility and RV is the historical realized volatility. Lowercase letters denote natural logs. We then estimate a prediction for implied volatility using the following equation:

$$\Delta\widehat{iv}_{i,t} = \widehat{\alpha}_t + \widehat{\beta}_{1t}\, iv_{i,t} + \widehat{\beta}_{2t}(iv_{i,t} - \overline{iv}_{i,t-11:t}) + \widehat{\beta}_{3t}(iv_{i,t} - rv_{i,t-11:t})$$

Stocks are sorted into deciles based on the difference between historical RV and the current IV. Decile ten consists of stocks with the highest (positive) difference while decile one consists of stocks predicted to have the lowest (negative) difference between these two volatility measures. Panel B reports statistics for these portfolios. We report formation-period volatilities and post-formation option returns. Option returns are computed using, as a reference beginning price, the option price computed from Black and Scholes formula using the predicted implied volatility ($\widehat{\text{IV}}$) and, as the closing price, the terminal payoff of the option depending on the stock price and the strike price of the option. All statistics are first averaged across stocks in each decile. The table reports the monthly averages of these cross-sectional averages for each reported number. The sample period is 1996 to 2005.

Panel A: Cross-sectional regression			
iv_{t-1}	$iv_{t-1} - \overline{iv}_{t-13:t-2}$	$iv_{t-1} - rv_{t-12:t-1}$	$\overline{R}^2$
-0.050	-0.257	-0.146	0.183
(-7.85)	(-27.90)	(-17.16)	

Panel B: Portfolios sorted on RV-IV											
Decile	1	2	3	4	5	6	7	8	9	10	10–1
					Formation period volatilities						
RV_t	0.403	0.423	0.441	0.450	0.468	0.489	0.510	0.534	0.574	0.688	–
$\widehat{\text{IV}}_t$	0.506	0.476	0.471	0.464	0.465	0.471	0.474	0.478	0.490	0.514	–
IV_t	0.563	0.503	0.489	0.474	0.470	0.472	0.470	0.467	0.470	0.476	–
					Post-formation returns						
Call	0.049	0.070	0.130	0.069	0.137	0.095	0.066	0.051	0.032	0.070	0.020
	(0.83)	(1.24)	(1.97)	(1.25)	(1.69)	(1.70)	(1.13)	(0.86)	(0.58)	(1.14)	(0.44)
Put	-0.156	-0.129	-0.173	-0.165	-0.157	-0.151	-0.112	-0.077	-0.152	-0.107	0.049
	(-2.65)	(-2.20)	(-3.01)	(-2.78)	(-2.75)	(-2.55)	(-1.81)	(-1.19)	(-2.72)	(-1.69)	(1.40)
Straddle	-0.049	-0.028	-0.044	-0.044	-0.029	-0.034	-0.033	-0.025	-0.047	-0.015	0.034
	(-2.67)	(-1.59)	(-2.56)	(-2.32)	(-1.48)	(-1.61)	(-1.68)	(-1.19)	(-2.47)	(-0.69)	(1.71)