Cross-Section of Option Returns and Volatility*

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Abstract

We study the cross-section of stock option return by constructing decile portfolios of straddles and delta-hedged calls and puts based on sorting stocks on the difference between historical realized volatility and at-the-money implied volatility. We find that a zero-cost trading strategy that is long (short) in the portfolio with a large positive (negative) difference between 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 option liquidity characteristics, and are not explained by usual risk factor models.

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Abstract

We study the cross-section of stock option return by constructing decile portfolios of straddles and delta-hedged calls and puts based on sorting stocks on the difference between historical realized volatility and at-the-money implied volatility. We find that a zero-cost trading strategy that is long (short) in the portfolio with a large positive (negative) difference between 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 option liquidity characteristics, and are not explained by usual risk factor models.

1 Introduction

Options give options. They allow an investor 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 these inputs. The most common options trading strategies involve the investor's view about the underlying volatility. In the vernacular of option traders, at the heart of every "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 the measurement and forecasting of realized volatility (RV) is extensive and too voluminous to cite in detail here.[1] A common finding reported by such studies is mean-reversion: volatility tends to revert to its long-run historical 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 between traders' expectations of future volatility and historical realized volatility are likely to be temporary. One forecast of future volatility is the implied volatility (IV), which can be obtained by inverting an option pricing model such as the Black and Scholes (1973) model.[2] Stocks for which IV is much lower than RV have 'cheap' options, and stocks for which IV is much higher than RV have 'expensive' options. Ex-ante, it is not obvious if these (cheap/expensive) options have different expected returns than options for which IV is close to RV. However, we speculate that, if there is volatility mispricing, it is more likely to manifest itself in extreme deviations between these two volatility estimates.

We, therefore, sort stocks into deciles based on the log difference between their one-year historical RV and their at-the-money (ATM) 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, ATM options. In order to partially

[1] The interested reader is referred to the recent surveys in Granger and Poon (2003) and Andersen, Bollerslev, Christoffersen, and Diebold (2006).

[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.

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. Having sorted the stocks by the log difference between RV and IV we form an option portfolio for each decile.

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, they have very little directional exposure to the underlying stocks. 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 generates statistically and economically significant returns. For example, a long-short portfolio of straddles yields a monthly average return of 21.9% and a Sharpe ratio of 0.626. These returns 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 statistically and economically significant positive returns for high decile portfolios and negative returns for low decile portfolios of delta-hedged calls and puts.

We then examine whether returns to the long-short strategy are related to aggregate risk and/or characteristics. We consider the expected returns on delta-hedged positions in the model of Duarte and Jones (2007). This model provides guidance in thinking about β's for (instantaneous) option returns. We use this model to compute theoretically expected returns and compare them to realized returns. We find that alphas from this framework are very close to raw returns. In fact, alphas from a more standard risk-factor model with standard equity-risk and option-risk factors are also very high.[3] We also explore whether stock/option characteristics are related to the variation in our portfolio returns, by cross-sectional regressions as well as via double sorted portfolios. Our analysis shows that, while the option returns covary with some of the stock characteristics that are found to be important for stock returns, this covariance is not enough to explain the high realized portfolio returns. It is possible that the profits to our volatility portfolios arise as compensation for some unknown aggregate risk. If such is indeed the case, the daunting task of formulating a cross-sectional options return model that accounts for our portfolios returns is left to future research.

Our results are robust to choice of sample periods as well as volatility measures. We,

[3] Although these regressions are linear factor models, we find that non-linear adjustments make virtually no difference. For instance, conditioning betas on option greeks or Leland (1999) model yields the no appreciable difference in alphas from standard alphas.

consistent with the literature on transaction costs on options markets, find that trading frictions reduce the profitability of the option portfolio strategy. For instance, the long-short straddle 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. Our analysis, therefore, shows that liquidity considerations reduce, but do not eliminate, the economically important profits of our portfolios.

The underlying reason for the empirical regularity that we observe in equity option prices is unclear. We reiterate that we cannot conclusively establish that our portfolio returns are abnormal, only that they are not related to obvious sources of risk. If, however, these returns are indeed abnormal, it is useful to consider why options are mispriced, especially given the significant size of the option market and the quality of option traders.[5] One potential reason is that investors overreact to the current information. Stein (1989) 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 results, where we find that stocks with low (high) current IV are the ones that we find the highest under(over)-pricing. Poteshman (2001) also finds evidence of overreaction in the index options market.

We find that while IV predicts future changes in volatility, changes in future realized volatility are smaller in magnitude than the changes in IV at portfolio formation. These facts, therefore, suggests that investors over-react to current events in their estimation of future volatility. For instance, it might be the case that investors ignore the systematic information contained in the *cross-section* of volatilities and over-weigh idiosyncratic events in forming expectations about future individual volatility. To test this conjecture, we form alternative real-time estimates of implied volatility using cross-sectional regressions. We use these alternative measures to recalculate option prices and find that these repriced options

[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`). Evidence that options traders are sophisticated investors is reported by Easley, O'Hara, and Srinivas (1998), Pan and Poteshman (2006), and Ni, Pan, and Poteshman (2006) who show that options' volume contains information about future stock prices.

do not lead to excess returns. Therefore, our results are also consistent with the hypothesis that there is valuable information contained in the cross-section of implied volatilities which is disregarded by option traders.

Our paper is related to the growing recent literature that analyzes trading in options. Coval and Shumway (2001) and Bakshi and Kapadia (2003) study trading in index options. Chava and Tookes (2006), Ni, Pan, and Poteshman (2006) and Ni (2006) study the impact of news/information on 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. Whether returns to option portfolios are related to fundamental risks and/or characteristics is investigated in Section 4. We present robustness checks as well as impact of trading frictions on portfolio profitability in Section 5. Section 6 presents a discussion of the results. We conclude in Section 7.

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 their IV and greeks for the period from 1996 to 2005. The IVs and greeks are calculated using a binomial tree model using Cox, Ross, and Rubinstein (1979).[6]

We apply a series of data filters to minimize the impact of recording errors. First we eliminate prices that violate arbitrage bounds. 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 non-trading, we eliminate from the sample all the observations for which both the bid and the ask are equal to the previous day quotes *and* for which their is no volume.

[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. 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.

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). In order to have continuous time series with constant maturity, we consider only those options that mature in the next month. Among these options with one month maturity, we then select the contracts which are closest to ATM. Since it is not always possible to select options with moneyness exactly equal to one, we only keep options with moneyness between 0.95 and 1.05. We, thus, select an option contract which is close to ATM and expires next month for each stock each month. After next month expiration, 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. For each stock, we obtain the IV estimate from one month to maturity, 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. RV is calculated using the standard deviation of realized daily stock returns over the most recent twelve months. 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 earnings announcements (Dubinsky and Johannes (2005)).

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 (implied volatility index that measures the markets expectation of 30-day S&P500 volatility implicit in the prices of near-term S&P500 options) 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).

3 Option Portfolio Strategies

Option prices are functions of observable (such as underlying price, expiration, moneyness etc.) and unobservable quantities (underlying volatility).[7] All option pricing models require, at least, an estimate of the parameters that characterize the probability distribution of future volatility. It is well known that volatility is highly mean-reverting – the autocorrelation for individual stock volatility in our sample is 0.7. This implies that large deviations of current volatility from it's long-term average are temporary in nature and are likely to reduce in magnitude at a quick rate (determined by the mean-reversion parameter). Any forecast of future volatility must account for this mean-reversion. One such forecast is embedded in the implied volatility of the stock.[8] Note that mean-reversion does *not* imply that, at any point in time, implied volatility should be the same (or close to) the long-term average of volatility. Indeed, differences in RV and IV are a necessary consequence of stochastic volatility. For instance, deviations of IV from RV will be more pronounced for stocks with higher volatility of volatility than for stocks with lower volatility of volatility.

[7]In a general equilibrium, the options prices are ultimately functions of fundamental quantities, such as investor utility function parameters. Therefore, our statement is strictly true only in partial equilibrium where, for instance, stock prices and market prices of risk have already been determined and are treated as exogenous parameters for pricing options.

[8]See footnote 2 for why this statement is only approximately true.

However, high autocorrelation of volatility implies that *large* deviations between RV and IV are unlikely to persist. Stocks for which IV is much lower than RV have 'cheap' options, and stocks for which IV is much higher than RV have 'expensive' options. We sort stocks into portfolios based on the difference between RV and IV and calculate returns on options in these portfolios. It is not obvious, ex-ante, whether there are differences in expected returns between these portfolios. However, we speculate that, if there is volatility mispricing, it is more likely to manifest itself in extreme deviations between these two volatility estimates.

3.1 Portfolios Descriptives

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 110 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 and IV, this also implies that IV is lower for higher deciles than that for lower deciles. Another illustration of the same phenomenon is call/put prices scaled by the stock price (last two rows of Table 2). 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 the average IV over the previous twelve months. Therefore, there are higher deviations of RV from IV in portfolio formation month than those in the prior months. In other words, portfolio formation month represents the month in which the IV of options in decile ten (one) increased (decreased) over it's normal level relative to RV.

There is not much variation (not accounted for by differences in IV's and underlying prices) in option greeks 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. The gammas (second derivative with respect to underlying price) and vegas (first derivative with respect to volatility) are of similar magnitude across deciles. We also estimate the volatility of volatility, ω, as the standard deviation of changes in daily implied volatilities during the six last months, and the correlation between stock returns and innovations to volatility, ρ, as the correlation between daily changes in implied volatility and stock returns over the last six months. We find that ω is higher for extreme portfolios than that for middle portfolios. This result is not surprising since larger deviations of IV (current volatility) from RV (long-term average of volatility) are more likely for those stocks with higher ω. Whether this difference in levels of ω has any systematic impact on (the returns of) the portfolios, however, depends on the sensitivity of these portfolios to risk factors. We discuss this issue later in the paper. Finally, we find that ρ is less negative for the first two deciles but shows, no appreciable pattern thereafter.

3.2 Portfolio Returns

We construct time series of calls, puts, straddles, and delta-hedged calls and puts 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 start trading a day after the day that we obtain the signal (difference between RV and IV). 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.

Since our interest is in studying returns on options based only on their volatility characteristics, we want to neutralize the impact of movements in the underlying stocks. There are two ways to accomplish this. One is through straddle portfolios and the other is

[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.

through delta-hedged portfolios. The advantage of latter relative to former is potentially lower transaction costs since stock trading is cheaper than options trading. We turn to the issue of execution costs in Section 5.2. The disadvantage is that straddle portfolios 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 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 the IVY database.[10] Table 3 reports the returns on option 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).[11] 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

[10]If there is volatility mispricing in options, a more powerful and profitable approach is to recalculate delta based on an implied volatility estimate. Green and Figlewski (1999) note 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.

[11]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 deciles five/six, this translates into an average return of 13% which is close to the sample average return of 12%.

large minimum return of –245% for calls leads to negative CE for these portfolios.

Straddle portfolios exhibit a striking pattern with returns that go from –12.4% to 9.5% respectively (Panel D). The volatility of the straddle portfolios is also low at between 17% and 26% per month. The long-short straddle strategy has an average return of 21.9% with 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 straddle 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.[12]

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 our sorting criterion still 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 option portfolios are close to zero (see Table 2), even with an average stock volatility of 50%, a return of –0.6% for the long-short stock portfolio is unlikely to account for the magnitude of the option portfolios.

In unreported results, we find that the portfolios constructed by sorting on the levels of RV (IV) do not produce the same patterns in average returns even though the signal is on average (inversely) related to the signal (see Table 2). While it is in general true that option portfolios of stocks with low realized volatility/high implied volatility (similar to decile one in Table 3) exhibit lower average returns than portfolios of stocks with high

[12]In addition to the simple straddle 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.

realized volatility/low implied volatility (similar to decile ten in Table 3), average returns for the long-short portfolios are often economically small and not statistically significant.

4 Controls for Risk and Characteristics

Our next task is to establish whether the large portfolio returns are systematic or abnormal. 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 general formal theoretical model for the cross-section of option returns, however, makes our endeavor non-trivial. We approach our problem from several different perspectives. We first consider the expected returns on delta-hedged positions in the model of Duarte and Jones (2007). This model, although stylized, provides guidance in thinking about β's for (instantaneous) option returns. We use this model to compute theoretically expected returns and compare them to realized returns and obtain an alpha in this framework. We then take the spirit of the model to run factor-model regressions with the standard equity-risk factors augmented with risk-factors for options. Next, we explore whether stock/option characteristics are related to the variation in our portfolio returns. This analysis is done on individual options via cross-sectional regressions, as well as via double sorted portfolios. We acknowledge that we (like others) are subject to joint hypothesis problem – the estimated 'alphas' are derived from models and, therefore, rejection of the null of zero alpha is a joint rejection of zero alphas and the model. Our hope is that these experiments taken *together* lend credence to our belief that the portfolio returns from previous section are not related to obvious sources of risk and characteristics.

4.1 Expected Returns

This subsection draws heavily upon Duarte and Jones (2007) and the interested reader is referred to their paper for further details. Individual stock return and volatility dynamics are related to those of market through a simple factor model. Analytical expressions are then derived for expected instantaneous returns on derivative positions. To be concrete, assume that the stock returns and volatility follow the process:

$$\begin{aligned} \frac{dS_t}{S_t} &= \mu_t\, dt + \sigma_t dB_{1t} \\ d\sigma_t &= \theta_t\, dt + \omega_t\, \rho\, dB_{1t} + \omega_t\, \sqrt{1-\rho^2} dB_{2t}\,, \end{aligned} \tag{1}$$

where B_1 and B_2 are uncorrelated Brownian motions. Here, volatility of volatility is represented by ω and ρ is the correlation between stock returns and volatility. We assume that the functional form of processes is the same for market and individual stocks (and suppress the superscripts in the above equations to reduce notational clutter). The relation between the Brownian motions for individual stocks and market is given by:

$$\begin{aligned} dB^i_{1t} &= \xi^i_{11} dB^m_{1t} + \xi^i_{12} dB^m_{2t} + dZ^i_{1t} \\ dB^i_{2t} &= \xi^i_{21} dB^m_{1t} + \xi^i_{22} dB^m_{2t} + dZ^i_{2t} \, , \end{aligned} \tag{2}$$

where ξ's represent correlations between Brownian motions driving the stock processes and market processes. Let λ_1 and λ_2 denote the prices of stock risk and volatility risk, respectively. Then it follows from the above equations that

$$\begin{aligned} \lambda^i_{1t} &= \xi^i_{11} \lambda^m_{1t} + \xi^i_{12} \lambda^m_{2t} \\ \lambda^i_{2t} &= \xi^i_{21} \lambda^m_{1t} + \xi^i_{22} \lambda^m_{2t} \, . \end{aligned} \tag{3}$$

Let the price of a derivative be given by $f(S_t, \sigma_t, t)$ and consider a total delta-hedged portfolio, H, with hedge ratio $n = -\left(\frac{\partial f}{\partial S} + \frac{\partial f}{\partial \sigma}\frac{\omega \rho}{\sigma S}\right) = -\left(\Delta + \nu \frac{\omega \rho}{\sigma S}\right)$. It can be shown that the excess return on this delta-hedged option is given by:

$$E\left(\frac{dH^i_t}{H^i_t}\right) - r_t dt = \omega^i_t \sqrt{1-\rho^{i2}} \lambda^i_{2t} \frac{1}{f^i_t} \frac{\partial f^i}{\partial \sigma^i_t} \, . \tag{4}$$

The estimation of the last equation is facilitated by expressing the expected returns in a beta representation. If β^i_{mt} and $\beta^i_{\sigma t}$ are the betas of total delta-hedged portfolio with respect to market and market volatility factor, respectively, then

$$\begin{aligned} \beta^i_{mt} &\equiv \text{cov}\left(\frac{\frac{dH^i}{H^i}}{\frac{1}{f^i}\frac{\partial f^i}{\partial \sigma^i}}, \frac{dS^m}{S^m}\right) \Big/ \text{var}\left(\frac{dS^m}{S^m}\right) = \frac{\omega^i_t \sqrt{1-\rho^{i2}} \xi^i_{21}}{\sigma^m_t} \\ \beta^i_{\sigma t} &\equiv \text{cov}\left(\frac{\frac{dH^i}{H^i}}{\frac{1}{f^i}\frac{\partial f^i}{\partial \sigma^i}}, \frac{\frac{dH^m}{H^m}}{\frac{1}{f^m}\frac{\partial f^m}{\partial \sigma^m}}\right) \Big/ \text{var}\left(\frac{\frac{dH^m}{H^m}}{\frac{1}{f^m}\frac{\partial f^m}{\partial \sigma^m}}\right) = \frac{\omega^i_t \sqrt{1-\rho^{i2}} \xi^i_{22}}{\omega^m_t \sqrt{1-\rho^{m2}}} \, . \end{aligned} \tag{5}$$

Subsituting equations (3) and (5) into equation (4), we finally obtain:

$$E\left(\frac{dH^i_t}{H^i_t}\right) - r_t dt = \frac{1}{f^i_t} \frac{\partial f^i_t}{\partial \sigma^i_t} \left(\beta^i_{mt} \sigma^m_t \; \lambda^m_{1t} + \beta^i_{\sigma t} \omega^m_t \sqrt{1-\rho^{m2}} \; \lambda^m_{2t}\right) dt \tag{6}$$

The last equation provides an analytical expression for instantaneous expected return on a total delta-hedged portfolio. We calculate the simple expected returns over an interval of a month by including a variance adjustment. The individual betas, β_m^i and β_σ^i, are estimated by running a first-pass time-series regression over the whole sample of scaled delta-hedged returns on the market portfolio return and scaled delta-hedged market portfolio return, respectively.[13] Market parameters are taken from Duarte and Jones (2007, Table 3). We report the betas, expected returns, actual returns, and the difference (alpha) for delta-hedged calls (puts) in Panel A (B) of Table 4.

While we find very little variation in β_σ across deciles, β_m is higher (less negative) for decile ten than it is for decile one. However, there is virtually no difference in expected returns across deciles. The realized returns, on the other hand, show a spread of 2.5% for calls and 2.6% for puts. Ergo, the abnormal returns (alphas) from this model are quite close to raw returns.

It is useful at this stage to juxtapose these results with the values of ω reported earlier in Table 2. We know that the extreme portfolios have higher volatility of volatility. However, what matters for expected returns, as evidenced in equations (4) and (6), is the sensitivity of these portfolios to volatility risk, β_σ. Our portfolios show no variation in exposure to this risk. Consequently, there is almost no variation in expected returns across these portfolios, even though they have different levels of ω. In other words, our portfolio returns are not a manifestation of the volatility of volatility effect.

4.2 Risk Adjusted Returns

We regress the long-short straddle and delta-hedged option portfolio returns on various specifications of a linear pricing model composed by the Fama and French (1993) three factors, the Carhart (1997) momentum factor, and a volatility factor. This last factor for straddle portfolios is the Coval and Shumway (2001) aggregate volatility factor represented by the excess return on a zero-beta S&P 500 index ATM straddle.[14] For delta-hedged call (put) portfolios, we construct a similar delta-hedged market call (put) factor. Since all the factors are spread traded portfolios, the intercept from these regressions can be interpreted as an alpha.

[13] The analytical expressions are for total delta-hedged returns. We use plain vanilla delta-hedged returns in this analysis as Duarte and Jones (2007) show that this delta adjustment has an insignificant impact. The results are, however, virtually unchanged for total delta-hedged portfolios. Note also that we, like Duarte and Jones, assume that the parameters of the model are constant in the empirical implementation.

[14] We obtain data on the first four factors from Ken French's web site while we construct the straddle factor ourselves following the procedure described in Coval and Shumway (2001). During our sample period, the return on the zero-beta S&P 500 index ATM straddle is −10.3% per month.

The factor model considered here is an improvement over the previous subsection in two ways. One, inclusion of non-market factors (such as SMB, HML, and MOM) is a generalization of the market model. Second, since we run time-series regressions on portfolio returns, the estimation error of imprecisely estimated individual betas is reduced. However, any linear factor model is unlikely to characterize the cross-section of option returns over any *discrete* time interval. 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 5. The first regression shows that the straddle portfolio has a negative loading on the market factor. Recall that decile ten consists of 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 French factors are negative (although insignificant) too and positive (again insignificant) for the momentum factor. The straddle portfolio loads positively on the zero-beta straddle portfolio. This coupled with the common assumption of a negative volatility risk premium implies that our strategy is a good hedge for volatility risk. Regressions (3)-(6) show similar pattern for delta-hedged calls and puts, although none of the loadings are significant.[15]

We also make efforts to ameliorate the problem associated with *linear* factor models in two ways. First, we estimate the following factor-model regressions with conditional betas:

$$R_{pt} = \alpha_p + \left(\beta_{0p} + \beta_{1p}' \Theta_{pt-1}\right)' F_t + e_{pt} \; , \tag{7}$$

where R is the return on portfolio, F's are factors, and Θ's are option greeks (delta, gamma, and vega). Conditional betas are used to proxy for the time-variation (over the life of the option) in expected returns of options. The alphas from this model are very similar to ones reported in Table 5. Second, we estimate Leland (1999) alpha. Leland proposes a correction to the linear factor models, that allows the computation of a robust risk measure for assets with arbitrary return distributions. This measure is based on an equilibrium model in which a CRRA investor holds the market. Our estimate of Leland's alphas are also very close to the ones reported in Table 5. For instance, Leland alpha for straddle portfolio is equal to 22.6%.

[15]Note that the betas in Table 5 are computed from unscaled returns while betas in Table 4 are computed from scaled returns, and are, therefore, not strictly comparable.

Overall, our results indicate that the portfolio returns reported earlier are not explained by the usual risk factors. However, we advise caution in over interpreting this evidence. The joint hypothesis problem is especially acute for us since there are *no* models for option returns over discrete time periods. What seems unambiguous is that the option portfolio returns are not related to *obvious* sources of risk and characteristics.

4.3 Stock Characteristics

We now investigate how the long-short straddle portfolio returns are related to equity characteristics. We first run cross-sectional regressions of risk-adjusted option returns on lagged characteristics. Specifically, our regressions specification is similar to that in Brennan, Chordia, and Subranmanyam (1998):

$$R_{it} - \widehat{\beta}_i' F_{it} = \gamma_{0t} + \gamma_{1t}' Z_{it-1} + e_{it} \,, \tag{8}$$

where R is the return on options (in excess of risk-free rate), F's are factors, and Z's are characteristics. The $\widehat{\beta}$'s on the left-hand side of the equation are estimated via a first-pass time-series regression using the entire sample. The factors are the same as in Section 4.2. Besides the primary variable of interest (RV–IV), the other characteristics chosen are: Size, book-to-market, past six-month return, volatility of volatility (ω), proportion of systematic risk (R^2), and analyst forecast dispersion. The first two of these are motivated by Fama and French (1992), the third one due to the evidence of momentum profits by Jegadeesh and Titman (1993),[16] and the fourth is based on the evidence reported earlier in Table 2 which shows that ω is related to the difference between RV and IV. We include R^2 since Duan and Wei (2007) find that systematic risk proportion is useful for cross-sectionally explaining the prices of equity options, and analyst dispersion because of the evidence in Diether, Malloy, and Scherbina (2002). Finally, two option characteristics (gamma and vega) are chosen to reflect information that is not directly contained in equities. All characteristics are lagged by one month in regressions.

We run these regressions every month and report the time-series averages of γ coefficients and their t-statistics in Table 6. The second through fifth column report various specifications for straddle returns while the last two columns report regressions results for delta-hedged calls and puts. Consistent with results in prior sections, the difference between RV and IV is strongly statistically significant in explaining the pattern of subse-

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

quent returns. Size, ω, R^2, and analyst forecast dispersion have insignificant coefficients for all options. The only stock characteristics that seem to have some predictive power are book-to-market and momentum returns. Even amongst these two, book-to-market is not significant for delta-hedged portfolios and momentum is not significant for delta-hedged calls. Finally, Γ and $\mathcal{V}$ have explanatory power only for straddles and delta-hedged puts.

We conclude that some of the characteristics are useful in explaining the cross-sectional pattern of option returns. However, the strongest determinant is the difference between RV and IV. The predictive power of this variable is not subsumed even after controlling for other characteristics (and risk-factors, via the left-hand side of the equation).

To provide yet another perspective of whether characteristics subsume our effect, we consider two-way sorts – one based on the volatility signal (RV–IV) and the second based on characteristics. The advantage of this approach over the cross-sectional regressions is that it does not impose any linear structure of returns (the disadvantage is that we can only control for one characteristic at one time). We sort stocks into quintile portfolios, as opposed to deciles, to keep the portfolios well populated. Our sorts are conditional - we first sort stocks into quintiles based on stock characteristics and, then, within each quintile we sort stocks based on the difference between RV and IV. The five volatility portfolios are then averaged over each of the five characteristic portfolios. They, thus, represent volatility portfolios controlling for characteristics. Breakpoints for all stock characteristics are calculated each month based only on stocks in our sample. We report average return and the associated t-statistic of this continuous time-series of monthly portfolio returns for straddles, delta-hedged calls, delta-hedged puts in Panels A, B, and C, respectively, of Table 7. In all three panels, we find that the magnitude of returns is very similar across all controls. It ranges from 15% to 17% for straddles, 1.6% to 1.8% to delta-hedged calls, and 1.7% to 2.0% for delta-hedged puts. These numbers are also comparable to those in Table 3, albeit a bit lower as expected (since we sort into quintiles in Table 7 as opposed to deciles in Table 3).

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

5 Robustness and Trading Execution

5.1 Robustness

The results in the previous sections are presented after we have made many choices about key variables and sample periods. In this section, we check whether our results our robust to these decisions. We only present the salient features of these tests to not overwhelm the readers with numbers (complete set of results can be obtained from us upon request).

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 two different states based on the sign of the changes in the VIX index and the sign of the market value-weighted CRSP portfolio returns. The conditional portfolio returns are higher in months in which VIX is increasing. For instance, the long-short straddle portfolio has returns of 28.9% in months of positive changes in VIX and 17.5% in months of negative changes in VIX. This pattern of returns also helps to explain the positive loading of long-short portfolio returns on options factors in Table 5. We obtain essentially the same result when we sort the sample based on market returns - option returns are higher in months of negative market returns. These two results are not completely independent since market returns and changes in VIX are negatively correlated.

When the sample is divided in the two subperiods 1996-2000 and 2001-2005 we observe that the 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.

Figure 1 shows that the equity option market was particularly active during the years of the "technology bubble." It is, therefore, useful to establish if portfolio returns are high only in the technology industry. In unreported results, we find this not to be the case. The long-short straddle 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 volatility sorted deciles and find this to be the case.

Volatility measures

Our basic measure of IV is the average of one-month ATM call and put IV. While it is necessary for us to calculate the IV's using the same options (same moneyness/maturity) that we trade, it is still possible that the IV is biased in other ways. We check for this possibility by rerunning our analysis with two modifications. First, we calculate the IV using only the call or the put. Second, our options are American - this implies that early exercise premium embedded in IV could make the IV measure not strictly comparable to RV. We check for this by removing all observations in which stock pays a dividend during the holding period.[17] The results of both these experiments are virtually identical to those reported in the paper. An alternative to the Black and Scholes implied volatility provided by IVY database is a model-free implied volatility (Jiang and Tian (2005)). This computation requires a large number of strikes for each stock at any point in time. The median number of strikes for options in our database is three. This implies that we can construct reliable estimates of model-free IV for a very small subset of stocks (for which there are at least ten strikes for each option). Our results are qualitatively similar for this restricted sample.

We *calculate* RV from daily stock return data. We do not use GARCH (or any versions, thereof) to *estimate* volatility as our purpose is not to forecast future volatility from calibrated models. We can use high-frequency intra-day data to potentially improve our measure of RV. However, unavailability of this data to us precludes us from doing this. Our hope is that there is no systematic bias in our use of daily data vis-à-vis intra-day data, especially since we calculate RV from a long time period of one year.

Earnings announcements

Dubinsky and Johannes (2005) find spikes in IV around earnings announcements. We check whether this influences our results again by running two tests. First, we remove observations where our trade dates coincide with earnings announcement dates (approximately 5% of observations). Second, we remove all observations where a company announces an earnings during the month prior to portfolio formation date or during the holding period month. Removing these observations has no material impact on our results. In addition to the above tests, we find that the earnings announcements are uniformly distributed in number across portfolios. Moreover, none of the portfolios show abnormally positive or negative earnings around these announcements - the SUE measure shows no pattern across deciles.

[17]We acknowledge the fact that while this controls for early exercise option of calls, American puts might still have a premium.

5.2 Transaction Costs

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.[18] It is essential to understand to what degree these frictions prevent an investor from exploiting the profits on the 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.

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 of all the option contracts traded on that stock during the previous month. We then sort stocks into terciles (low, medium and high liquidity) based on these characteristics and calculate average returns and t-statistics for the long-short straddle portfolios for these three groups of stocks. We report the results of these computations for straddle portfolios in Panel A of Table 8.

Portfolio returns decrease substantially, as expected, after taking transaction costs into account. The long-short straddle portfolio returns are reduced from 21.9% to 4.1% per month if we consider trading options at an effective spread equal to the quoted spread.

[18] 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).

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 obtained by sorting on the average bid-ask spread of options. The returns, computed from mid-points, to the long-short straddle 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 the options average daily trading volume.

The conjecture that trading costs might be lower for delta-hedged portfolios than for straddle portfolios is investigated in detail in Panel B of Table 8. We consider the transaction costs of trading options only and assume that stock 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.[19] The pattern of higher returns for more illiquid options found in Panel A is repeated Panel B. 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

[19] 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).

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.[20] We also find that the profitability of option portfolios is higher for less liquid options.

6 Discussion

We have shown that (large) differences between RV and IV predict future option returns. We now explore whether these deviations of IV from RV are temporary, as we conjectured earlier in the paper, and what are the determinants of these deviations.

We first analyze the patten of volatilities before and after portfolio formation month. We plot the level of IV and the difference of RV and IV twelve months before and after portfolio formation date for the extreme deciles in Figure 2. By construction, decile one (ten) consists of stocks with large negative (positive) differences between RV and IV at time 0. Table 2 also shows that IV in decile one (ten) is higher (lower) than it's own twelve-month moving average. These facts are re-confirmed in the figure. However, the figure also shows a striking pattern of IV *after* portfolio formation. IV for decile one (ten) decreases (increases) after portfolio formation almost as quickly as it increases (decreases) in the months preceding the portfolio formation date. These pattern of changes in IV are not accompanied by similar pattern of changes in RV – the deviations of RV and IV are the highest at time 0 (by construction) and are insignificant a year before and after portfolio formation. These results show that deviations of RV from IV are indeed not persistent.

What leads to these temporary deviations? We know that some of the 'causes' are fundamental - for instance, high volatility of volatility is naturally associated with large swings in volatility (see Table 2). However, some of the reasons are more proximate. Stocks in decile one (ten) have negative (positive) returns in the month immediately preceding the portfolio formation date. Investors, cognizant of the asymmetric volatility (Black (1976)) effect, will revise upwards (downwards) their estimates of future volatility for stocks in decile one (ten). In unreported results, we find that the realized volatility in the month subsequent to portfolio formation does increase (decrease) for decile one (ten). Therefore, IV predicts future changes in volatility. However, changes in future realized volatility

[20]Please 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.

are smaller in magnitude than the changes in IV at portfolio formation. These facts, therefore, suggests that investors over-react to current events in their estimation of future volatility. For instance, it might be the case that investors ignore the systematic information contained in the *cross-section* of volatilities and over-weigh idiosyncratic events in forming expectations about future individual volatility. To test this conjecture, we form alternative real-time estimates of implied volatility using cross-sectional regressions. We want to use these alternative measures to recalculate option prices and check whether these repriced options lead to excess returns.

As a first step in this exercise, 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:

$$\Delta iv_{i,t} = \alpha_t + \beta_{1t}\, iv_{i,t-1} + \beta_{2t}(iv_{i,t-1} - \overline{iv}_{i,t-13:t-2}) + \beta_{3t}(iv_{i,t-1} - rv_{i,t-12:t-1}) + \epsilon_{i,t}\ , \qquad (9)$$

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, $rv_{i,t-12:t-1}$ is the natural logarithm of the historical realized volatility (calculated using months $t-12$ to $t-1$) for stock i. Our model is motivated by the existing empirical evidence of a high degree of mean-reversion in realized volatility, and by the evidence presented in the previous subsections. In addition to the volatility signal (log difference between RV and IV) we include the log level of implied volatility as well as the log difference between the level of implied volatility and its twelve months moving average. We predict the log change in implied volatility, instead of the level, to avoid the possibility of predicting a negative level. We estimate a Fama and MacBeth (1973) regression wherein each cross-sectional estimate is computed on the 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 9. 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 in a real time fashion:

$$\Delta \widehat{iv}_{i,t} \;=\; \widehat{\alpha}_t + \widehat{\beta}_{1t}\, iv_{i,t} + \widehat{\beta}_{2t}(iv_{i,t} - \overline{iv}_{i,t-12:t-1}) + \widehat{\beta}_{3t}(iv_{i,t} - rv_{i,t-11:t}). \qquad (10)$$

The above equation is a direct analog of equation (9) except that we use the current month's variables on the right hand side of equation (10) in order to use the most recent information for our prediction: we use IV and RV measures available at t and parameter estimates also obtained at time t. We obtain the prediction of the implied volatility level ($\widehat{\text{IV}}_{i,t}$) in the following way:

$$\widehat{\text{IV}}_{i,t} = \text{IV}_{i,t} \times e^{\Delta \widehat{iv}_{i,t}}.$$

Panel B of Table 9 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 $\widehat{\text{IV}}$ is indeed higher (lower) than IV for decile ten (one). The economic implication of this alternative estimate of implied volatility is then pursued by repricing the options involved in the portfolio strategies by plugging the $\widehat{\text{IV}}$ estimate into the Black-Scholes model. We find that, while preserving the original sorting, returns on long-short portfolios of delta-hedged calls/puts and straddles, computed using the "recalculated" prices, are both economically and statistically insignificant.

Please note that, since the options are American, the Black-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 volatility (option price) mis-estimation. These results are consistent with our hypothesis that there is valuable information contained in the cross-section of implied volatilities which is disregarded by option traders.

7 Conclusion

We emphasize that our results do not depend on the validity of the Black and Scholes (1973) or the Cox, Ross, and Rubinstein (1979) model. Implied volatilities should be interpreted as representation of option prices. Therefore the reader should view our portfolio sorts as sorts on option prices with decile one (ten) representing cheap (expensive) 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 the existence of a substantial spread in the cross-section of U.S. equity options sorted on a very simple criterion.

The underlying reason for the empirical regularity that we observe in equity option prices is unclear. While we find that our option returns are not related to obvious sources of risk, we can not conclusively establish that these are true 'alphas.' It is possible that the profits to our volatility portfolios arise as compensation for some unknown aggregate risk. If such is indeed the case, the daunting task of formulating a cross-sectional options return model that accounts for our portfolios returns is left to future research.

If, instead, these returns are abnormal, this raises the question of what accounts for this volatility mispricing. It may be 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 miss-estimate the mean reversion parameter in the underlying stochastic volatility and, therefore, incorrectly price the option. The fact that the alternative implied volatility estimates computed from our cross-sectional model eliminate the portfolio profitability 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.

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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.

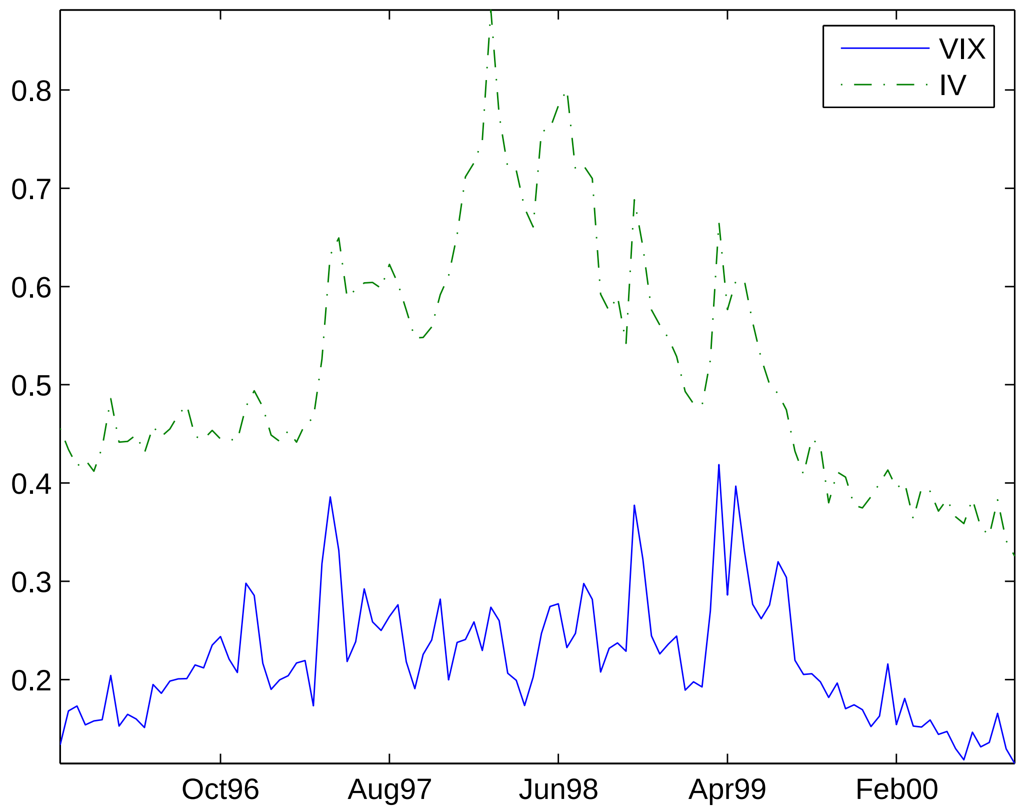
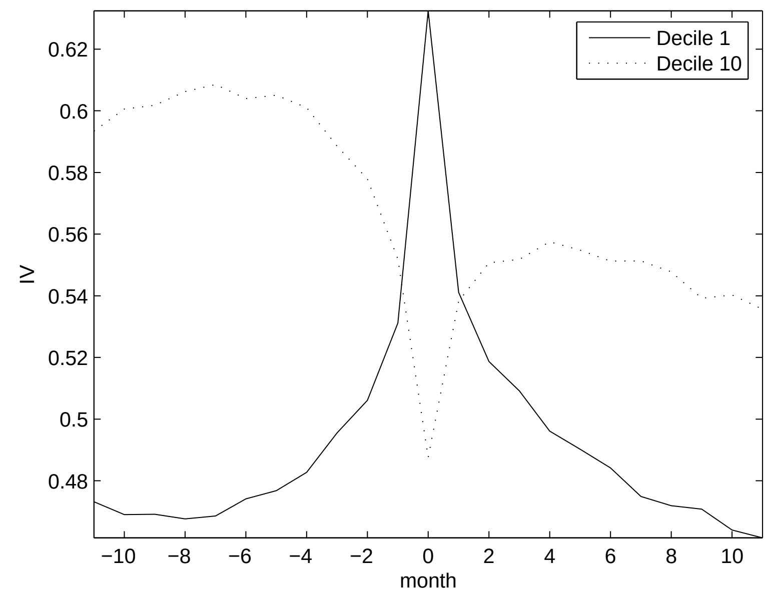


Figure 2: Volatilities Before and After Portfolio Formation

Portfolios are formed as in Table 2. We plot the IV (in Panel A) and the difference in RV and IV (in Panel B) for a period of twelve months before to twelve months after portfolio formation.

Panel A: IV



Panel B: RV-IV

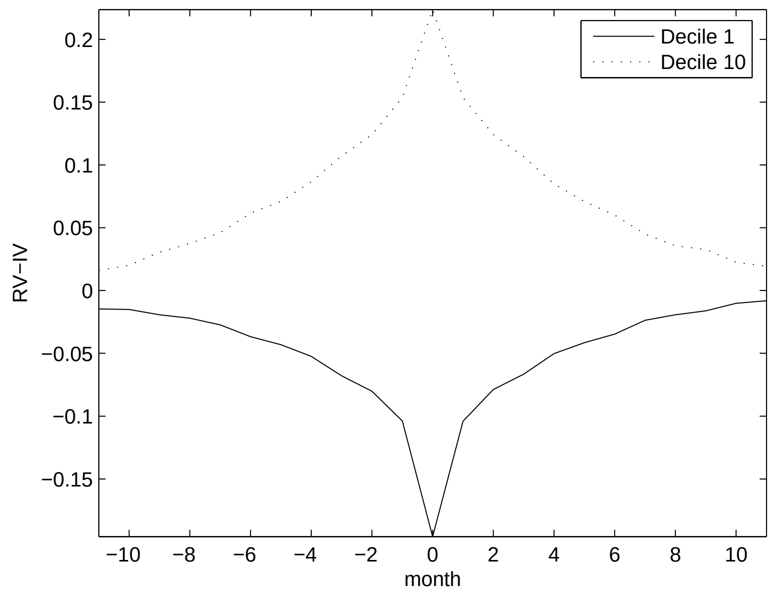


Table 1: Summary Statistics

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), 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. RV is calculated using the standard deviation of realized daily stock returns over the most recent twelve months. 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: Formation-Period Statistics of Portfolios Sorted on the Difference Between RV and IV

We sort stocks into deciles based on the difference between the historical RV and the current IV. Decile ten consists of stocks with the highest (positive) log difference while decile one consists of stocks predicted to have the lowest (negative) log difference between RV and IV. The table reports the formation period statistics on these portfolios. All statistics are first averaged across stocks in each decile (the time-series average number of stocks in each decile is 110). The table reports the monthly averages of these cross-sectional averages for each reported number. ω is the volatility of volatility calculated using standard deviation of daily implied volatilities during the six last months and ρ is the correlation between daily changes in implied volatility and stock returns calculated using the last six months. Δ, Γ, and $\mathcal{V}$ are the delta, gamma, and vega, respectively, of the options. C/S (P/S) is the call (put) to stock price ratio. The sample period is 1996 to 2005.

Decile	1	2	3	4	5	6	7	8	9	10
$\text{RV}_t - \text{IV}_t$	-0.193	-0.095	-0.059	-0.032	-0.009	0.014	0.038	0.066	0.104	0.211
RV_t	0.415	0.439	0.453	0.471	0.484	0.505	0.526	0.552	0.583	0.678
IV_t	0.608	0.534	0.512	0.503	0.493	0.491	0.488	0.486	0.479	0.467
$\overline{\text{IV}}_{t-12:t-1}$	0.475	0.481	0.484	0.492	0.498	0.508	0.518	0.533	0.549	0.591
Δ^c	0.555	0.549	0.543	0.539	0.534	0.529	0.527	0.525	0.522	0.520
Δ^p	-0.450	-0.456	-0.462	-0.466	-0.471	-0.475	-0.478	-0.480	-0.483	-0.487
Γ	0.117	0.118	0.120	0.121	0.123	0.125	0.127	0.131	0.138	0.154
$\mathcal{V}$	3.531	3.778	3.864	3.882	3.846	3.863	3.733	3.660	3.544	3.312
ω	0.033	0.028	0.027	0.026	0.026	0.027	0.027	0.028	0.030	0.036
ρ	-0.221	-0.244	-0.259	-0.267	-0.273	-0.281	-0.286	-0.285	-0.285	-0.272
C/S	0.063	0.058	0.055	0.054	0.053	0.052	0.052	0.051	0.051	0.051
P/S	0.060	0.054	0.052	0.052	0.051	0.052	0.052	0.052	0.052	0.054

Table 3: Option Portfolios' Returns

Portfolios are formed as in Table 2. 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	-0.001	0.052	0.079	0.081	0.109	0.130	0.131	0.109	0.147	0.231	0.232
std	0.562	0.601	0.613	0.589	0.624	0.655	0.667	0.656	0.670	0.761	0.493
min	-0.907	-0.928	-0.896	-0.960	-0.967	-0.916	-0.958	-0.959	-0.977	-0.957	-1.150
max	2.102	2.032	2.056	1.625	2.150	2.150	2.531	1.985	1.813	2.929	2.267
SR	-0.007	0.082	0.124	0.132	0.170	0.195	0.191	0.162	0.215	0.300	0.471
CE ($\gamma = 3$)	-0.522	-0.592	-0.543	-0.667	-0.720	-0.550	-0.678	-0.727	-0.774	-0.692	-0.240
CE ($\gamma = 7$)	-0.798	-0.856	-0.796	-0.912	-0.926	-0.823	-0.907	-0.915	-0.948	-0.905	-0.681
					Panel B: Put Returns						
mean	-0.294	-0.251	-0.221	-0.185	-0.179	-0.156	-0.108	-0.089	-0.078	-0.000	0.294
std	0.540	0.581	0.606	0.638	0.651	0.653	0.669	0.658	0.656	0.768	0.395
min	-0.932	-0.883	-0.899	-0.885	-0.891	-0.935	-0.912	-0.911	-0.954	-0.893	-0.488
max	2.435	2.769	2.546	3.462	3.161	3.112	2.692	2.890	2.616	3.615	1.604
SR	-0.550	-0.436	-0.369	-0.295	-0.280	-0.243	-0.166	-0.140	-0.123	-0.004	0.743
CE ($\gamma = 3$)	-0.705	-0.661	-0.659	-0.592	-0.602	-0.654	-0.600	-0.586	-0.683	-0.558	0.139
CE ($\gamma = 7$)	-0.858	-0.794	-0.806	-0.766	-0.773	-0.859	-0.810	-0.811	-0.899	-0.771	-0.043

Decile	1	2	3	4	5	6	7	8	9	10	10–1
Panel C: Stock returns											
mean	0.016	0.014	0.014	0.014	0.015	0.013	0.012	0.009	0.011	0.010	-0.006
std	0.061	0.057	0.060	0.058	0.063	0.065	0.066	0.067	0.068	0.076	0.043
min	-0.173	-0.193	-0.185	-0.197	-0.227	-0.217	-0.215	-0.248	-0.232	-0.234	-0.189
max	0.164	0.137	0.160	0.163	0.178	0.194	0.236	0.164	0.201	0.302	0.159
SR	0.218	0.195	0.184	0.200	0.193	0.151	0.135	0.092	0.120	0.094	-0.144
CE ($\gamma = 3$)	0.011	0.009	0.008	0.009	0.009	0.006	0.005	0.002	0.004	0.001	-0.009
CE ($\gamma = 7$)	0.003	0.001	0.000	0.002	-0.001	-0.004	-0.005	-0.009	-0.007	-0.012	-0.014
Panel D: Straddle Returns											
mean	-0.125	-0.085	-0.064	-0.034	-0.023	-0.019	-0.004	0.012	0.032	0.098	0.224
std	0.180	0.183	0.194	0.203	0.203	0.229	0.224	0.223	0.224	0.266	0.213
min	-0.497	-0.415	-0.396	-0.352	-0.433	-0.344	-0.453	-0.425	-0.368	-0.349	-0.204
max	0.616	0.876	0.821	0.929	0.998	1.223	1.081	1.158	1.092	1.255	0.892
SR	-0.714	-0.483	-0.348	-0.184	-0.128	-0.095	-0.031	0.040	0.130	0.358	1.051
CE ($\gamma = 3$)	-0.173	-0.130	-0.110	-0.083	-0.072	-0.074	-0.060	-0.043	-0.023	0.025	0.172
CE ($\gamma = 7$)	-0.229	-0.177	-0.156	-0.130	-0.123	-0.124	-0.129	-0.106	-0.082	-0.051	0.110
Panel E: Delta-Hedged Call Returns											
mean	-0.016	-0.010	-0.008	-0.007	-0.005	-0.003	0.000	0.000	0.003	0.009	0.025
std	0.025	0.028	0.026	0.022	0.023	0.025	0.029	0.026	0.026	0.032	0.031
min	-0.064	-0.058	-0.075	-0.051	-0.051	-0.045	-0.055	-0.048	-0.057	-0.058	-0.064
max	0.088	0.111	0.128	0.107	0.126	0.135	0.139	0.147	0.139	0.148	0.134
SR	-0.772	-0.468	-0.424	-0.464	-0.340	-0.224	-0.089	-0.102	0.011	0.196	0.823
CE ($\gamma = 3$)	-0.017	-0.011	-0.009	-0.008	-0.006	-0.004	-0.001	-0.001	0.002	0.008	0.024
CE ($\gamma = 7$)	-0.018	-0.012	-0.010	-0.009	-0.007	-0.005	-0.002	-0.002	0.001	0.006	0.022
Panel F: Delta-Hedged Put Returns											
mean	-0.016	-0.012	-0.008	-0.005	-0.002	-0.001	0.000	0.002	0.004	0.010	0.026
std	0.022	0.021	0.021	0.020	0.021	0.021	0.022	0.021	0.021	0.028	0.025
min	-0.072	-0.081	-0.088	-0.037	-0.042	-0.047	-0.052	-0.043	-0.036	-0.043	-0.021
max	0.092	0.094	0.089	0.110	0.118	0.111	0.098	0.114	0.094	0.142	0.126
SR	-0.876	-0.719	-0.519	-0.383	-0.259	-0.196	-0.116	-0.065	0.032	0.250	1.047
CE ($\gamma = 3$)	-0.017	-0.012	-0.008	-0.005	-0.003	-0.002	-0.000	0.001	0.003	0.009	0.025
CE ($\gamma = 7$)	-0.018	-0.013	-0.009	-0.006	-0.004	-0.003	-0.001	0.000	0.002	0.008	0.024

Table 4: Expected Option Returns

This table presents expected returns on delta-hedged calls and puts. The individual stock returns follow a one-factor model and the market return has stochastic volatility. Both stock-risk and volatility risk are priced. Further details are in the text. The expected return on a delta-hedged option in this model is given by:

$$E\left(\frac{dH_t^i}{H_t^i}\right) - r_t dt = \frac{1}{f_i}\,\frac{\partial f_i}{\partial \sigma_t^i}\left(\beta_{mt}^i \sigma_t^m\ \lambda_{1t}^m + \beta_{\sigma t}^i \omega_t^m \sqrt{1-\rho^{m2}}\ \lambda_{2t}^m\right) dt\ ,$$

where $\lambda's$ are prices of risk, ρ is the correlation between the Brownian motions for return and volatility processes, ω is the volatility of volatility. The betas, β_m and β_σ, are estimated from regressions of scaled delta-hedged option returns on the market portfolio return and scaled delta-hedged market portfolio return, respectively. Returns are scaled by $\frac{1}{f}\,\frac{\partial f}{\partial \sigma}$. The market parameters used are: $\lambda_1^m = 0.16$, $\lambda_2^m = -0.12$, $\sigma^m = 0.06$, $\omega^m = 0.05/\sqrt{12}$, and $\rho^m = -0.7$. The row titled $E[H_i]$ gives the expected return based on above equation (the expected 'monthly' return in the table is adjusted for the variance term). The row titled $\overline{H_i}$ is the actual return and α is the difference between the actual and the expected return. Actual returns on portfolios are the same as in Table 3. Portfolios are formed as in Table 2. The sample period is 1996 to 2005.

Decile	1	2	3	4	5	6	7	8	9	10	10–1
					Panel A: Delta-Hedge Calls						
β^c_{mkt}	-0.352	-0.324	-0.300	-0.310	-0.293	-0.299	-0.282	-0.283	-0.235	-0.250	0.102
β^c_{vix}	0.264	0.270	0.279	0.274	0.278	0.282	0.283	0.279	0.267	0.255	-0.008
$E[H^c]$	-0.004	-0.004	-0.005	-0.006	-0.006	-0.006	-0.007	-0.006	-0.006	-0.006	-0.002
$\overline{H^c}$	-0.016	-0.010	-0.008	-0.007	-0.005	-0.003	0.000	0.000	0.003	0.009	0.025
α	-0.013	-0.004	-0.002	-0.001	0.002	0.004	0.007	0.007	0.008	0.015	0.028
					Panel B: Delta-Hedge Puts						
β^p_{mkt}	-0.239	-0.211	-0.199	-0.180	-0.182	-0.168	-0.150	-0.174	-0.130	-0.191	0.048
β^p_{vix}	0.198	0.195	0.203	0.197	0.195	0.201	0.193	0.188	0.182	0.182	-0.016
$E[H^p]$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001	0.000	-0.006	-0.003
$\overline{H^p}$	-0.016	-0.012	-0.008	-0.005	-0.002	-0.001	0.000	0.002	0.004	0.010	0.026
α	-0.014	-0.009	-0.005	-0.003	-0.000	-0.000	0.001	0.003	0.003	0.016	0.030

Table 5: Risk-Adjusted Option Returns

Portfolios are formed as in Table 2. 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 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 S&P 500 straddle factor (ZBSTRAD-Rf). DHCALL and DHPUT are S&P 500 delta-hedged call and put factor returns. The first row gives the coefficient while the second row gives the t-statistics in parenthesis. The sample period is 1996 to 2005.

	Straddles		Delta-Hedged			
			Calls		Puts	
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.237	0.243	0.028	0.026	0.026	0.026
	(12.07)	(12.59)	(9.12)	(7.43)	(10.09)	(9.65)
MKT – Rf	-0.866	-1.223	-0.088	-0.047	-0.024	-0.023
	(-1.63)	(-2.08)	(-1.11)	(-0.63)	(-0.30)	(-0.31)
SMB		-0.323		-0.084		-0.055
		(-0.44)		(-0.73)		(-0.50)
HML		-1.090		0.016		-0.023
		(-1.64)		(0.13)		(-0.21)
MOM		0.093		0.104		0.006
		(0.19)		(1.05)		(0.09)
ZBSTRAD – Rf	0.081	0.072				
	(3.25)	(3.01)				
DHCALL – Rf			0.151	0.119		
			(1.39)	(1.23)		
DHPUT – Rf					0.031	0.023
					(0.32)	(0.26)
$\overline{R}^2$	0.114	0.114	0.036	0.041	-0.013	-0.035

Table 6: Option Returns Controlling for Stock Characteristics (Fama-Macbeth Regressions)

Each month, we regress risk-adjusted option returns on a number of stocks characteristics. The risk-adjusted returns are calculated by subtracting factor model expected returns from raw returns. The factors used in risk-adjustment are the Fama and French (1993) factors, momentum factor, and an option factor. The option factors are ZBSTRAD-Rf, DHCALL, and DHPUT for straddles, delta-hedged calls, and delta-hedged puts, respectively. $rv-iv$ is the log difference of RV and IV, Size is the market capitalization, BtoM is the book-to-market, Mom is the last six-month cumulative return, ω is the volatility of volatility, R^2 is from the market model regression, Disper is the dispersion in analyst forecasts, and Γ and $\mathcal{V}$ are the option gamma and vega, respectively. Returns on options are constructed based on the same procedure as in Table 3. The table reports the average coefficient and the associated t-statistic from the monthly Fama-Macbeth regressions on individual options (straddles, delta-hedged calls, delta-hedged puts). The last row gives the average $\overline{R}^2$ from the monthly regressions. The sample period is 1996 to 2005.

	Straddles				Delta-Hedged	
					Calls	Puts
	(1)	(2)	(3)	(4)	(5)	(6)
const	-0.001	0.040	-0.004	-0.039	-0.025	-0.009
	(-0.09)	(0.79)	(-0.08)	(-0.69)	(-3.24)	(-1.53)
$rv-iv$	0.241	0.237	0.224	0.206	0.022	0.023
	(10.46)	(9.79)	(8.96)	(8.39)	(7.71)	(9.62)
Size		-0.003	-0.001	-0.001	0.001	-0.000
		(-1.00)	(-0.21)	(-0.41)	(2.17)	(-1.34)
BtoM		0.025	0.050	0.020	0.001	-0.002
		(1.18)	(2.19)	(0.89)	(0.37)	(-0.89)
Mom		-0.011	-0.033	-0.031	0.002	-0.003
		(-0.85)	(-2.33)	(-2.27)	(0.60)	(-1.98)
ω			-0.309	-0.288	0.050	-0.007
			(-0.89)	(-0.81)	(1.07)	(-0.19)
R^2			0.007	0.022	-0.003	0.003
			(0.12)	(0.42)	(-0.58)	(0.73)
Disper			1.158	1.038	0.168	0.031
			(1.62)	(1.41)	(1.40)	(0.39)
Γ				0.154	0.006	0.057
				(3.26)	(0.21)	(6.07)
$\mathcal{V}$				0.002	-0.001	0.001
				(1.55)	(-0.62)	(5.96)
$\overline{R}^2$	0.006	0.016	0.024	0.027	0.030	0.032

Table 7: Option Returns Controlling for Stock Characteristics (Double Portfolio Sorts)

Each month, we first sort stocks into quintiles based on stock characteristics and then, within each quintile we sort stocks based on the difference between the historical RV and the current IV (as in Table 2). The five volatility portfolios are then averaged over each of the five characteristic portfolios. They, thus, represent volatility portfolios controlling for characteristics. For volatility sorts, quintile five consists of stocks with the highest (positive) log difference while quintile one consists of stocks predicted to have the lowest (negative) log difference between these two volatility measures. Beta is the stock beta calculated from the market model using last 60 months, Size is the market capitalization, BtoM is the book-to-market, Mom is the last six-month cumulative return, ω is the volatility of volatility, R^2 is from the market model regression, Disper is the dispersion in analyst forecasts. Breakpoints for all 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 table reports the average return and the associated t-statistic of this continuous time-series of monthly returns. The sample period is 1996 to 2005.

	Volatility quintile					
Control	1	2	3	4	5	5–1
			Panel A: Straddle Returns			
Beta	-0.097	-0.047	-0.022	-0.006	0.051	0.148
	(-6.19)	(-2.64)	(-1.10)	(-0.31)	(2.40)	(10.14)
Size	-0.102	-0.039	-0.020	0.003	0.065	0.168
	(-6.76)	(-2.34)	(-1.06)	(0.15)	(2.93)	(10.81)
BtoM	-0.100	-0.040	-0.021	0.003	0.065	0.165
	(-6.32)	(-2.23)	(-1.06)	(0.17)	(3.03)	(10.91)
Mom	-0.098	-0.042	-0.020	0.008	0.058	0.156
	(-6.44)	(-2.47)	(-1.01)	(0.40)	(2.78)	(10.70)
ω	-0.096	-0.039	-0.012	0.018	0.056	0.151
	(-6.65)	(-2.34)	(-0.69)	(0.89)	(2.63)	(9.90)
R^2	-0.101	-0.041	-0.022	-0.002	0.054	0.155
	(-6.15)	(-2.31)	(-1.13)	(-0.11)	(2.48)	(9.69)
Disper	-0.102	-0.038	-0.022	0.004	0.064	0.166
	(-6.62)	(-2.18)	(-1.10)	(0.21)	(2.99)	(10.76)

	Volatility quintile					
Control	1	2	3	4	5	5–1
	Panel B: Delta-Hedged Call Returns					
Beta	-0.013	-0.006	-0.004	-0.000	0.004	0.016
	(-5.56)	(-2.90)	(-1.73)	(-0.20)	(1.85)	(9.04)
Size	-0.012	-0.006	-0.003	0.001	0.007	0.018
	(-6.07)	(-3.09)	(-1.54)	(0.21)	(2.63)	(8.78)
BtoM	-0.013	-0.007	-0.003	0.000	0.006	0.018
	(-6.36)	(-3.48)	(-1.35)	(0.19)	(2.37)	(9.33)
Mom	-0.011	-0.007	-0.003	0.002	0.006	0.017
	(-5.52)	(-3.45)	(-1.27)	(0.83)	(2.33)	(7.95)
ω	-0.011	-0.006	-0.001	0.003	0.006	0.017
	(-5.25)	(-2.63)	(-0.42)	(1.10)	(2.30)	(6.88)
R^2	-0.013	-0.006	-0.004	-0.000	0.004	0.017
	(-5.77)	(-2.65)	(-1.80)	(-0.16)	(1.83)	(8.25)
Disper	-0.012	-0.006	-0.003	0.001	0.006	0.018
	(-6.06)	(-2.97)	(-1.43)	(0.38)	(2.54)	(8.28)
	Panel C: Delta-Hedged Put Returns					
Beta	-0.013	-0.005	-0.002	-0.000	0.004	0.017
	(-7.32)	(-2.97)	(-1.16)	(-0.13)	(2.48)	(13.22)
Size	-0.013	-0.005	-0.002	0.001	0.007	0.020
	(-7.53)	(-2.69)	(-1.11)	(0.50)	(3.30)	(12.57)
BtoM	-0.013	-0.005	-0.002	0.001	0.006	0.019
	(-7.61)	(-3.00)	(-1.11)	(0.39)	(3.10)	(12.36)
Mom	-0.013	-0.005	-0.001	0.002	0.006	0.019
	(-7.30)	(-3.07)	(-0.74)	(0.91)	(2.97)	(11.72)
ω	-0.013	-0.005	-0.001	0.003	0.006	0.019
	(-7.31)	(-2.56)	(-0.36)	(1.28)	(2.89)	(10.71)
R^2	-0.013	-0.005	-0.002	-0.000	0.004	0.017
	(-7.21)	(-2.69)	(-1.10)	(-0.04)	(2.51)	(11.78)
Disper	-0.013	-0.005	-0.002	0.001	0.007	0.020
	(-7.45)	(-2.50)	(-1.20)	(0.73)	(3.20)	(11.85)

Table 8: 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) log difference while decile one consists of stocks predicted to have the lowest (negative) log difference between RV and IV. 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 straddle 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 straddle 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 9: Cross-Sectional Model for Predicting Implied Volatility

Panel A reports the time-series averages of the following Fama and MacBeth (1973) regression (t-statistics adjusted for serial correlation are reported 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 log difference between historical RV and the current IV (as in Table 2). 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	0.415	0.439	0.453	0.471	0.484	0.505	0.526	0.552	0.583	0.678	–
$\widehat{\text{IV}}_t$	0.530	0.499	0.491	0.489	0.487	0.491	0.494	0.500	0.504	0.515	–
IV_t	0.608	0.534	0.512	0.503	0.493	0.491	0.488	0.486	0.479	0.467	–
Post-formation returns											
Straddles	-0.026	-0.003	-0.043	-0.042	-0.028	-0.034	-0.033	-0.025	-0.066	-0.035	-0.009
	(-1.37)	(-0.17)	(-2.49)	(-2.27)	(-1.43)	(-1.62)	(-1.67)	(-1.21)	(-3.48)	(-1.59)	(-0.44)
Delta-hedged Calls	-0.009	-0.004	-0.008	-0.008	-0.007	-0.006	-0.006	-0.005	-0.010	-0.008	0.000
	(-3.40)	(-2.17)	(-4.00)	(-3.90)	(-3.19)	(-2.57)	(-2.51)	(-2.26)	(-4.09)	(-2.87)	(0.14)
Delta-hedged Puts	-0.003	0.000	-0.003	-0.003	-0.001	-0.002	-0.000	-0.000	-0.005	-0.002	0.001
	(-1.26)	(0.01)	(-1.63)	(-1.59)	(-0.29)	(-0.75)	(-0.17)	(-0.12)	(-2.67)	(-0.77)	(0.35)