# Option Returns and the Cross-Sectional Predictability of Implied Volatility*

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**Abstract**

We study the cross-section of realized stock option returns and find an economically important source of predictability in the cross-sectional distribution of implied volatility. A zero-cost trading strategy that is long (short) in straddles with a large positive (negative) forecast of the change in implied volatility forecast produces an economically important and statistically significant average monthly return. The results are robust to different market conditions, to firm risk-characteristics, to various industry groupings, to options liquidity characteristics, and are not explained by linear factor models. Compared to the market prediction, the implied volatility estimate obtained from the cross-sectional forecasting model is a more precise and efficient estimate of future realized volatility.

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# 1 Introduction

Volatility is central to the pricing of options as contracts on more volatile stocks are more expensive than those on less volatile stocks, *ceteris paribus*. An accurate prediction of future volatility, therefore, delivers important economic information to traders. It is not surprising that there is an extensive literature on predicting volatility. The future volatility of stocks is usually predicted using weighted averages of historical actual realized volatility, variants of GARCH models, range-based approaches, and options implied volatility (IV).[1] Granger and Poon (2003) survey the extant literature and conclude that the market forecast embedded in IV is the best forecast of future realized volatility. However, most studies focus on predicting the volatility of a single asset (frequently the S&P 500 index) using *time-series* methods. Instead, we directly examine the behavior of the *cross-section* of implied volatilities of all U.S. equity options. We show that there is important information in the cross-section of stock implied volatilities that leads to better predictions of future volatility than those provided by the market's IV itself. To the best of our knowledge, this is the first paper to investigate the predictability of the cross-section of individual equity option implied volatilities.

We obtain IV estimates from one month to maturity, at-the-money options since these are the most liquid contracts. Doing so also ensures that, across stocks, our sample is homogenous with respect to the contract characteristics. Since IV of at-the-money options is directly related to the underlying volatility, it carries similar statistical properties as it is very persistent. We use a system of Fama and MacBeth (1973) cross-sectional regressions to estimate a mean-reversion cross-sectional model of IV augmented with variables that improve the forecasting power. We find that a stock with an IV below the cross-sectional average and below its own twelve-month moving average has a higher IV in the next month. Similarly, a stock with IV above the cross-sectional average and above its own twelve-month moving average has a lower IV in the next month. Thus, cross-sectional regressions indicate a high degree of mean-reversion in implied volatilities.

We then study the economic implications of these forecasts through options portfolio strategies. We use the out-of-sample volatility predictions produced by the cross-sectional forecasting model to sort stocks into deciles. We calculate equally-weighted portfolio monthly returns on calls and puts on stocks in each decile. To minimize the impact of microstructure effects, we eliminate stale quotes and skip a day between the

[1] The literature is too voluminous to cite here. For an incomplete list, see Alizadeh, Brandt, and Diebold (2002), Andersen, Bollerslev, Diebold, and Ebens (2001), Bollerslev, Chou, and Kroner (1992), Christensen and Prabhala (1998), French, Schwert, and Stambaugh (1989), and Schwert (1989).

estimation of the forecasts and portfolio formation. We find that all of these portfolios are quite profitable. Calls and puts portfolios have high average returns which, however, are marked by high volatility that leads to low Sharpe ratios and negative certainty equivalents. A zero-cost trading strategy, involving a long position in a portfolio of options with a large predicted increase in volatility and a short position in a portfolio of options with a large predicted decrease in volatility, is very attractive. For instance, the monthly Sharpe ratio of the calls (puts) long-short portfolio is 0.435 (0.134). We also calculate equally-weighted monthly returns on straddles. Since at-the-money straddles have very low deltas, they are postulated to benefit from the volatility forecast more directly than calls or puts. We find this to be the case as straddles portfolios still have high returns but considerably lower volatility than portfolios of calls or puts. A long-short portfolio of straddles has a monthly Sharpe ratio of 0.626. The returns to straddles portfolios are comparable to those in Coval and Shumway (2001), who report absolute returns of around 3% per week for zero-beta straddles on the S&P 500.

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

We also examine whether returns to the long-short strategy are related to aggregate risk. We use linear factor models comprising the Fama and French (1993) factors, the Carhart (1997) momentum factor, and an aggregate volatility factor proxied by changes in VIX.[2] We find that the return on the long-short straddles portfolio is negatively related to movements in the three stock market factors. This suggests that the long-short strategy is attractive because it hedges the sources of aggregate risk that are priced in the stock market. The return on the straddles portfolio is also positively related to the changes in VIX. Since a volatility premium explanation would predict a negative loading on $\Delta$VIX, a positive loading implies that the long-short straddles portfolio is

[2]Option payoffs are non-linearly related to payoffs of stocks. Therefore, a linear factor model is unlikely to characterize the cross-section of option returns. We use a linear model merely to illustrate that the option returns described in this paper are not related to aggregate sources of risk in an obvious way.

also a good hedge for volatility risk.

There is an extensive literature that documents that transaction costs in the options market are quite large.[3] We also find that trading frictions reduce the attractiveness of our portfolio strategy. For instance, the long-short straddles portfolio returns are reduced to 5.3% per month if we consider trading options at an effective spread equal to one-half of the quoted spread. In the extreme scenario wherein effective spreads are equal to quoted spreads, the profits disappear.[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.

Although most of our analysis is devoted to straddles portfolios, we also study delta-hedged portfolios. Delta-hedged calls/puts portfolios are less profitable than the straddles portfolios since the former benefit from volatility mispricing of calls *or* puts while the latter benefit from volatility mispricing of calls *and* puts. Nevertheless, we find that the volatility predictability lends itself to positive returns for high decile portfolios and negative returns for low decile portfolios of delta-hedged calls/puts. An additional advantage of delta-hedging is lower transaction costs, since these lead to positive and statistically significant trading profits even after accounting for very high transaction costs.

To summarize, we find that implied volatility predictability leads to economically large profits. This prompts us to investigate the source of these profits. IV from an option is the market's estimate of future volatility of the underlying asset. However, we find that our estimate of future implied volatility is better than IV at predicting the future realized volatility of the underlying stock. Since the option's value is related to the underlying future volatility over the life of the option, this provides the underlying economic rationale for the trading profits reported in the previous section.

The market for equity options is active and has grown constantly over the thirty years of its existence. There is also evidence that options traders are sophisticated investors. Easley, O'Hara, and Srinivas (1998) and Pan and Poteshman (2006) show that options' volume contains information about future stock prices. Given the significant

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

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

size of the market[5] and the quality of option traders, it is useful to consider why option implied volatilities are predictable. One reason may be that the economic agents do not use all the available information in forming expectations about future stock volatilities. In particular, they might ignore the information contained in the cross-sectional distribution of implied volatilities and consider assets individually when forecasting volatility. The cross-sectional forecasts obtained in this paper have characteristics similar to those of shrinkage estimators even though they are not formally constructed using Bayesian shrinkage techniques. Another possibility is that the investors overreact to the current information, which is consistent with the findings of Stein (1989).[6] Stein studies the term structure of the implied volatility of index options and finds that investors overreact to the current information. They ignore the long-run mean reversion in implied volatility and instead overweight the current short-term implied volatility in their estimates of long-term implied volatility. Stein's finding is analogous to our cross-sectional results, where we find that stocks with low (high) current IV are the ones that we predict to have the highest under(over)-pricing in implied volatility.

In an informationally efficient market, prices (implied volatilities) should not be predictable. To the contrary, the evidence presented in this paper suggests that the information contained in our forecast of implied volatility (based on readily available data) allows one to construct profitable trading strategies. In the context of the stock market, post-earnings-announcement drift strategies (Ball and Brown (1968)) and momentum strategies (Jegadeesh and Titman (1993)) have been identified by Fama (1998) as among those posing the most serious challenge to market efficiency. This paper extends this list by identifying the existence of similar strategies in the hitherto unexplored area of options markets.

The rest of the paper is organized as follows. The next section discusses the data. Section 3 contains a description of the IV forecasting model and results of the estimation. In Section 4, we study the economic content of the volatility forecasts by analyzing the performance of portfolios of options formed by sorting the forecasts. We undertake further tests in Section 5 to improve our understanding of the source of the trading profits. Section 6 concludes.

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[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. These figures are taken from the Options Clearing Corporation 2004 annual report, which can be found at `http://www.optionsclearing.com/about/ann_rep/ann_rep_pdf/annual_rep_04.pdf`.

[6]Poteshman (2001) also studies the term structure of various estimates of IV. He arrives at the conclusion that inefficiencies exist but does not explore their economic magnitude.

## 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 implied volatilities (IVs) and deltas for the period from January 1996 to May 2005. The IVs and deltas are calculated using a binomial tree model using Cox, Ross, and Rubinstein (1979). Stock options are traded at the American Stock Exchange, the Boston Options Exchange, the Chicago Board Options Exchange, the International Securities Exchange, the Pacific Stock Exchange, and the Philadelphia Stock Exchange.[7]

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

We construct a cross-sectional predictive model for options IVs. The regressions in these models are estimated on the first trading day (usually a Monday) immediately following the expiration Saturday of the month (all the options expire on the Saturday immediately following the third Friday of the expiration month). At any point in time, equity options have traded maturities corresponding to the two near-term months plus two additional months from the January, February or March quarterly cycles. In order to have continuous time series with constant maturity, we consider only those options that mature in the next month. This criterion guarantees that all the option contracts selected have the same maturity of approximately one month. Among these options with one month maturity, we then select the contracts which are closest to at-the-money (ATM). Since strike prices are spaced every \$2.5 apart when the strike price is between \$5 and \$25, \$5 apart when the strike price is between \$25 and \$200, and \$10

[7]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.

apart when the strike price is over $200, it is not always possible to select option with exactly the desired moneyness. Options with moneyness lower than 0.95 or higher than 1.05 are eliminated from the sample. We, thus, select an option contract which is close to ATM and expires next month for each stock each month. After expiration the next month, a new option contract with the same characteristics is selected. Our final sample is composed of 81,296 monthly observations. The average moneyness for calls and puts is very close to one. There are 4,249 stocks in the sample for which it is possible to construct at least one IV observation to use in regressions.

We report summary statistics for IV and the annualized realized volatility (RV) of the underlying stocks in Table 1. IV is computed as the average of the implied volatilities extracted from the call and the put contracts, selected based on the maturity/moneyness filter following the procedure described above. RV is computed as the standard deviation of daily realized returns of the underlying stock (from CRSP database) for the period corresponding to the maturity of the option. We first compute the time-series average of these volatilities for each stock and then report the cross-sectional average of these average volatilities. The other statistics are computed in a similar fashion so that the numbers reported in the table are the cross-sectional averages of the time-series statistics, and these can be interpreted as the summary statistics on an "average" stock.

Both IV and RV are close to each other, with values of 58.2% and 55.2% 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. Finally, IV surface exhibits a mild smirk — the 20% OTM put IV ($SmL$) is 7.4% higher than the ATM volatility, while the 20% OTM call IV ($SmR$) is 2.2% higher than the ATM volatility.[8]

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 $\Delta$IV 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.

[8]For a detailed discussion of the theoretical and empirical relation between the slope of the volatility surface and the properties of the risk-neutral distribution see Bakshi, Kapadia, and Madam (2003), Das and Sundaram (1999), Dennis and Mayhew (2002), and Toft and Prucyk (1997).

Spikes in individual stock IV also happen on the occasion of earnings announcements (Dubisnky and Johannes (2005)).[9]

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

However, the two variables differ in an important way – the average stock IV is more persistent than VIX. The autocorrelation coefficient of the average IV is equal to 0.944; the same coefficient is 0.714 for VIX. This high degree of persistence in stock IV is the central feature of the forecasting model for stock's IV that is developed in the next section. 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. The monthly correlation between the underlying asset return and change in IV is –0.52 for index options and –0.33, on average, for individual stocks (see Dennis, Mayhew, and Stivers (2005) for further discussion of this result).

# 3 Predicting Implied Volatility

The bulk of the finance literature has focused on forecasting the realized volatility of a single asset using a time-series approach. The future volatility of stocks is usually predicted using weighted averages of historical actual realized volatility (calculated using daily or intra-day data), variants of GARCH models, range-based approaches, and options IV. Granger and Poon (2003) survey the extant literature and broadly find that the market's forecast embedded in IV is the best forecast of future realized volatility for stocks. These studies, however, focus mainly on predicting the realized volatility of a single asset (frequently the S&P 500 index) using time-series methods.

We, on the other hand, use a cross-sectional regression to forecast the distribution of implied volatilities. In other words, our innovation for volatility forecasting is two-fold. First, we study the predictability of implied volatility embedded in options (as opposed

[9] Approximately 5% of our observations are also earnings announcement dates (as reported by IBES). Removing these observations has no material impact on our results.

to realized volatility of the underlying stock). Second, we use cross-sectional methods (as opposed to time-series methods). We focus on implied volatilities because of the direct dependence of option prices on implied volatilities.

## 3.1 Model Specification

Our cross-sectional approach to forecasting implied volatility is similar to that of Jegadeesh (1990), who identifies predictable patterns in the cross-section of stock returns. Each month $t$, we specify the forecasting model as follows:

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

where $iv_{i,t}$ is the natural logarithm of the ATM IV for stock $i$ measured at month $t$, $\overline{iv}_{i,t-13:t-2}$ is the natural logarithm of the twelve months moving average of $\text{IV}_i$, $\overline{rv}_{i,t-13:t-2}$ is the natural logarithm of the twelve months moving average of the realized volatility for stock $i$, and $N$ is the number of stocks in month $t$.

Our model is motivated primarily by the existing empirical evidence of a high degree of mean-reversion in realized volatility, both at the aggregate and individual stock level (see Granger and Poon (2003) and Andersen, Bollerslev, Christoffersen, and Diebold (2006) for comprehensive reviews). The twelve-month average of IV is included because lags beyond than the first one could contain valuable information. We include an average rather than all the lags because the average is a conservative way of using all available information: it involves estimating only one parameter, instead of the twelve parameters corresponding to the twelve lags, and it does not lead to data loss when one of the lags is missing. Finally, realized volatility is included as an additional regressor because it could provide incremental information over IV.[10]

We forecast the change in IV because it is the relevant variable in constructing option strategies. This forecast is, however, equivalent to forecasting the level of IV. We also choose to work in logs, instead of levels, because in this way we avoid the problem of having to truncate the negative fitted values in the prediction of the level of volatility.

An alternative to the cross-sectional forecasting model is to estimate a similar time-series model for each individual stock. Since each of these time-series regressions is

[10]We also experiment by using smiles of options, industry dummies, and stock characteristics (such as previous month return, beta, size, and book-to-market ratio) as additional explanatory variables. The marginal explanatory power and economic significance of all these factors are negligible.

noisy, individual slope coefficients can be cross-sectionally averaged to obtain reliable beta coefficients in the same way as in equation (1). We use this approach too and find very similar results to the ones reported in our paper. We still follow the cross-sectional approach in the paper because of several reasons. First, the cross-sectional approach is arguably simpler than the time-series approach. Second, stocks for which we do not have sufficient observations (20 quarters) to estimate a time-series can still be included in the cross-section. Third, the cross-section allows us to estimate the regressions in a real-time fashion with no look-ahead bias (this is important for the portfolio strategies studied later in this paper). Fourth, the cross-sectional regressions can be used to estimate the standard errors on the regression coefficients. This is a non-trivial task for time-series regressions because the cross-correlations in residuals across stocks leads to the correlation of individual slope coefficients. Fifth and last, the cross-sectional model avoids the problem of determining the unconditional mean of each stock's volatility, leaving a much simpler task of estimating the conditional cross-sectional average.

We proceed by estimating a Fama and MacBeth (1973) cross-sectional regression at each date $t$ (Monday following the third Friday of the month). We tabulate averages of the cross-sectional estimates and $t$-statistics adjusted for serial correlation in Table 2. We also report measures of in-sample and out-of-sample fit of these regressions. The in-sample fit is measured by the $\overline{R}_t^2$ of each monthly cross-sectional regression. We report the time-series average and standard deviation of $\overline{R}_t^2$. As a measure of out-of-sample performance, we compute Root Mean Square Errors (RMSE) for each stock $i$ as $\text{RMSE}_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\widehat{iv}_{i,t\to t+1} - iv_{i,t+1})^2}$, where $\widehat{iv}_{i,t\to t+1}$ is the predicted value of implied volatility at time $t+1$ based on the regression at time $t$. $\text{RMSE}_i$ measures the deviation of forecasts from actual changes in volatility in a true out-of-sample experiment. We report its cross-sectional average and standard deviation.

## 3.2 Cross-Sectional Regression Results

Specification (1) in Table 2 shows that an increase in IV is negatively related to the lagged level of IV, which implies that stocks' implied volatilities revert towards the cross-sectional mean: a high level of volatility today, compared to the cross-sectional average, predicts a lower IV in the future, or a negative change. The estimated coefficient of –0.084 is highly statistically significant and implies a cross-auto-correlation coefficient for the level of IV of 0.916 that is very close to the estimate obtained from the time series of cross-sectional averages.

Specification (2) shows that the coefficient on the difference between the current level of IV and the twelve-month average is negative and largely significant, suggesting that the mean reversion property of the individual time-series of IV is also an important factor in predicting the future change in IV. The richer dynamic of the second model leads to a higher average $\overline{R}^2$ and a lower average RMSE. A similar conclusion can be drawn from specification (3) wherein the difference between the current level of IV and the twelve-month moving average of realized volatility is considered. The best forecasting model is the fourth model wherein the two measures of past volatility are concurrently used as a predictor. In this model, the change in IV is negatively related to the last period IV and negatively related to both moving averages. The average $\overline{R}^2$ is quite large at 18.5%, and at times it is as high as 50%. Model (4) has also the lowest average RMSE, equal to 15.9%, confirming that the better in-sample performance is not due to overfitting the data. The forecasts produced by this model are used for the rest of the analysis in the paper.

One interesting result from the estimation of the forecasting model is that the accuracy of the predictions, either in and out of sample, is negatively related to changes in the aggregate level of volatility, VIX. The monthly correlation between the time series of $\overline{R}^2$ and changes in VIX is equal to –0.38, while the correlation between the time series of cross-sectional averages of square deviations of the out-of-sample forecasts from the actual changes and the changes in VIX is 0.32. This suggests that the changes in the cross-section of implied volatilities are more difficult to forecast when the VIX is increasing.

### 3.3 Portfolios Based on Cross-Sectional Regressions

The regression model of the previous subsection indicates a high degree of predictability in the cross-sectional distribution of changes in IV. However, the RMSE of the regression shows that forecasts for individual stock volatility are still fairly noisy. One way of using the information from the cross-sectional regressions while maximizing the signal-to-noise ratio is to form portfolios.

We compute a prediction of each stock's implied volatility at the beginning of each month in a real time fashion. We use implied and realized volatility measures available at month $t$ and parameter estimates of equation (1) obtained from month $t$ to obtain a prediction of implied volatility for the next month $t + 1$. We label this prediction as

$\widehat{\text{IV}}_{i,t\to t+1}$ and calculate it using the equation

$$\Delta\widehat{iv}_{i,t\to t+1} \equiv \widehat{iv}_{i,t\to t+1} - iv_{i,t} = \widehat{\alpha}_t + \widehat{\beta}'_t\,[iv_{i,t}\ ,\ iv_{i,t} - \overline{iv}_{i,t-12:t-1}\ ,\ iv_{i,t} - \overline{rv}_{i,t-12:t-1}], \quad (2)$$

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

We then form decile portfolios by ranking stocks based on the difference between $\widehat{\text{IV}}_{i,t\to t+1}$ and $\text{IV}_{i,t}$. Decile ten consists of stocks that are predicted to have the highest (positive) percentage change in IV while decile one consists of stocks that are predicted to have the lowest (negative) percentage change in IV. The advantage of forming portfolios is that a cardinal signal of predicted value is transformed into a potentially more precise ordinal signal on the ranking of predicted values.

We give descriptive statistics on these deciles in Table 3. 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. Proceeding from decile one to decile ten, the market capitalization of the underlying stock increases while the IV decreases. These features are, of course, complementary: larger stocks are typically less volatile than smaller stocks. However, we also see that the further the market's IV is from that of the past measures of IV, the higher (in absolute value) the predicted difference is in implied volatility. For instance, the difference between the level of $\text{IV}_{i,t}$ and the cross-sectional mean of implied volatility ($\overline{\text{IV}}_t$) is 11.5% and –8.5% for deciles one and ten. Similarly, the difference between $\text{IV}_{i,t}$ and the twelve-months moving average of past implied volatility ($\overline{\text{IV}}_i$) is 15.4% for decile one and –12.1% for decile ten. This analysis confirms that the predictability in IV is related to both the cross-sectional and the time-series mean reversion.

We also calculate two statistics on the post-formation performance of volatility forecasts. Specifically, we report the mean of the out-of-sample predicted change (in levels), $\Delta\widehat{\text{IV}}_{i,t\to t+1}$, as well as of the actual change, $\Delta\text{IV}_{i,t+1}$. The two averages are remarkably close. For example, the average forecast for decile one is –8.0% while the actual change is –7.0%. Similarly the forecast for decile ten is 4.1% while the actual change is 4.0%.[11]

[11] The predicted change in volatility of about 4.0% for decile ten indicates the underpricing of call options. Back-of-the-envelope calculations suggest that this results in underpricing of about 7.8% for an ATM call expiring in one month, with a riskfree rate of 3% and IV of 50%. These rough calculations are close to the actual magnitude of the returns presented in the next section. See also the discussion in Section 5.

Moreover, the predicted/actual changes in volatility increase monotonically as we go from decile one to decile ten. Since the sorting of stocks into deciles each month is done in the out-of-sample fashion (relying only on coefficient estimates available at the time), this further confirms the fact that the superior performance of the forecasting model of equation (1) is not due to data overfitting.

## 3.4 Forecasts of Future Realized Volatility

We use an approach similar to that of Christensen and Prabhala (1998) to test the hypothesis that $\widehat{\mathrm{IV}}$ is a better predictor, than the market forecast IV, of the future realized volatility.[12] We run a horse race by estimating the regression model

$$RV_{t+1} = \alpha + \beta X_t + \epsilon_{t+1} \ , \qquad (3)$$

where $RV$ is the future realized volatility of the stock over the life of the option, and $X_t$ is either the predicted $\widehat{\mathrm{IV}}_{t \to t+1}$ or the current $\mathrm{IV}_t$. The realized volatility is calculated using daily returns on stock over the life of the option (one month). The underlying hypothesis is that if the forecast is unbiased the parameters $\alpha$ and $\beta$ should be equal to zero and one, respectively. In evaluating which volatility measure is a better forecast of realized volatility we apply three criteria: which one has a smaller forecast error, in this case measured by the intercept; which measure has a slope which is closer to one; and, finally, which forecasting model has the higher average $\overline{R}^2$.

Table 4 reports the estimation results. In the first panel we report the results of the time series analysis wherein we estimate the coefficients of equation (3) for each stock using the entire available sample. The analysis delivers a pair of estimated parameters $(\hat{\alpha}_i, \hat{\beta}_i)_{i=1}^N$ for each stock. We tabulate the cross-sectional mean of the coefficients as well as the standard deviation of the cross-sectional distribution (in curly brackets). In the second panel, we tabulate the results of the analysis when equation (3) is estimated cross-sectionally. Average parameters and $t$-statistics (in parenthesis) corrected for serial dependence are shown in Panel B of the table.

Both panels of Table 4 offer the same evidence that $\widehat{\mathrm{IV}}$ is a better predictor of future realized volatility than IV. In both the time-series and the cross-sectional approach model (1) has a smaller $\hat{\alpha}$, a larger $\hat{\beta}$, and a higher average $\overline{R}^2$. For example, in the

[12] See, also Day and Lewis (1992), Canina and Figlewski (1993), Fleming (1998), Lamoureux and Lastrapes (1993), and Jiang and Tian (2005) for other studies of the relation between IV and future realized volatility.

time series regression, $\hat{\alpha}$ is closer to zero, $\hat{\beta}$ is closer to one, and $\overline{R}^2$ is higher for model (1) than for model (2) in 64%, 65%, and 73%, respectively, of the cases.[13] In the Fama-MacBeth regression the estimated intercept in model (1) is very small (0.002) and not statistically different from zero, while the slope estimated coefficient is 0.956 and not statistically different from one. In this context inference about the differences in the estimated coefficients from across models is directly possible. The mean difference of the constants (–0.044) is statistically different from zero with a $t$-statistic, corrected for serial dependence, of –9.7. Similarly the mean difference in the slopes (0.110) has a $t$-statistic of 12.6.

# 4 Option Portfolio Strategies

The previous section shows that our cross-sectional regression model generates reliable estimates of future implied volatility, especially for portfolios. Equally importantly, the forecast of future implied volatility, $\widehat{\mathrm{IV}}_{i,t\to t+1}$, is a better predictor than $\mathrm{IV}_{i,t}$ of future realized volatility $\mathrm{RV}_{i,t+1}$. Since the forecast of future volatility of underlying stock is one of the most important determinants of option prices, it's predictability can be economically significant to investors. In this section we investigate this possibility by analyzing the returns on option portfolios formed on the basis of the implied volatility prediction.

We construct time series of call, put, and straddle 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). In this section, we also initiate option portfolio strategies on the second (Tuesday), as opposed to the first (Monday), trading day after expiration Friday of the month. In other words, we skip a day after the day that we obtain the signal (difference between $\widehat{\mathrm{IV}}$ and IV) for sorting stocks. This is to further ensure that microstructure biases in the data do not impact our results. 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 expiration day

[13]In general, standard inference on the cross-sectional distribution of estimated parameters is not easily available, because the estimates are likely to be cross-correlated. If we assume that the estimates are not cross-correlated, both the difference in the constant from model (1) and (2), 0.017, and the difference in the slope, 0.037, are highly statistically significant with $t$-statistics of –7.1 and 7.9, respectively.

stock price and the strike price of the option.[14] 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.

To form portfolios, we sort stocks into deciles in the same way as in Section 3.3 by ranking stocks based on the difference between $\widehat{\mathrm{IV}}_{i,t\to t+1}$ and $\mathrm{IV}_{i,t}$. Decile ten consists of stocks predicted to have the highest (positive) percentage change in IV while decile one consists of stocks predicted to have the lowest (negative) percentage change in IV. Based on Section 3.4, one can also regard stocks in decile ten (one) as those for which our estimate of realized volatility is higher (lower) than that of the market. Equally-weighted monthly returns on calls, puts, straddles, and underlying stocks of each portfolio are computed and the procedure is then repeated for every month in the sample. On average, the portfolios contain 110 stock options in each month.

Table 5 reports the results of this exercise. The pattern in the portfolio average returns is in line with the predicted change in implied volatility. Decile one has negative average monthly returns equal to –4.6%, –1.0%, and –4.6% for calls, puts, and straddles, respectively. The average returns increase monotonically as one goes from decile one to decile ten. Decile ten has average returns equal to 21.0%, 5.7%, and 10.3% for calls, puts, and straddles, respectively.

The call and put portfolios are, however, characterized by very high volatility that ranges from 54% to 83% per month. The volatility of the straddles portfolios is much lower at between 18% and 28% per month. We also 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 ($\gamma$) 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 straddles portfolio for decile ten, on the other hand, has high SR and CE.

The returns to a long-short strategy, that is long in decile ten and short in decile one,

[14] 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 portfolio and upwards for the short portfolios. The net effect is not clear. See Poteshman and Serbin (2003) for a discussion of early exercise behavior.

are noteworthy. The long-short call and put portfolios have high average returns and volatility that are generally lower than that of either portfolio in decile one or ten, leading to large monthly SR equal to 0.435 and 0.134 for calls and puts, respectively. However, the very large minimum return of –70% and –168% for call and put, respectively, leads to negative CE for these long-short portfolios. In contrast, the long-short staddle strategy has an average return of 15.0% with a 23.9% monthly standard deviation (the minimum monthly return in the sample is –41.3%), leading to a monthly SR of 0.626 and a CE($\gamma = 3$) of 8.0% per month. An increase in the risk aversion parameter to seven, however, leads to a negative CE. The returns to the straddles portfolios are comparable to those in Coval and Shumway (2001, Table III), who report absolute returns of around 3% per week for zero-beta straddles S&P 500. To put 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.

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 as we go from decile one to decile ten. However, since the delta of at-the-money straddles is close to zero, stock returns of –0.9% for the long-short portfolio are unlikely to account for the magnitude of long-short straddles portfolio average returns of 15.0%. Note also that the results do not appear to be driven by microstructure effects. Since the returns are computed from the mid-point prices they are not affected by the bid-ask bounce effect of Roll (1984). Additionally, we remove stale quotes and skip a day in computing option returns. Altogether the evidence confirms that the ability to predict implied volatility leads to high option returns. The long-short straddles portfolio returns are statistically significant and economically large.

Since straddles returns are most clearly related to the source of predictability, we focus only on the straddles portfolios in the remainder of this paper.[15]

## 4.1 Sub-Sample Returns

We replicate the analysis of Table 5 by dividing the data into two sub-samples. The sub-samples are formed by considering different states of the VIX and the aggregate market return. The states are determined by the sign of the changes in the VIX index and by the sign of the market value-weighted CRSP portfolio returns. Mean returns and

[15]Results for portfolios of calls and puts, which are qualitatively similar, can be obtained from the authors upon request.

$t$-statistics of the long-short straddles portfolio in these different states are reported in Table 6.

Panel A of Table 6 shows how the portfolio returns differ in periods of increasing and decreasing VIX. The conditional portfolio returns are higher in months in which VIX is increasing. The return difference across these two states of the world increases moving from decile one to decile ten. The average return difference is virtually zero for decile one and 18.2% for portfolio ten. In four of the ten portfolios this difference is significantly greater than zero. The long-short strategy has returns of 26.8% in months of positive changes in VIX and 8.5% in months of negative changes in VIX.

Note that we divide the sample in Panel A based on VIX (and not average IV) changes. It is, however, plausible to assume that there is "commonality" in volatility and that change in IV of an average stock is correlated with changes in VIX. Since options have a positive return when volatility increases, it is not surprising that higher decile portfolios have greater returns when VIX is increasing. The fact that the high decile portfolios also have low *current* IV makes them benefit especially from an increase in volatility.[16] By the same token, the returns on lower decile portfolios are not significantly negative in states of the world in which VIX is increasing. The flip side of the coin is that lower decile portfolios have significantly negative returns and higher decile portfolios have insignificantly positive returns when VIX is decreasing. The net result, however, is that the difference in returns between these two states is significant only for higher decile portfolios.

In Panel B the sample is divided according to the sign of the market return. Decile one has higher average returns when the market is rising, while the opposite is true for decile ten. The return difference between positive and negative market periods decreases with the size of the predicted change in IV. For the long-short portfolio the spread between up and down market is equal to –13.7% and statistically significant. This effect obtains for essentially the same reason as that in Panel A because market returns and VIX are negatively correlated.

Untabulated results for portfolios of calls and puts differ in only one dimension: the call long-short portfolio has a much higher average return (19.5%) when the market is up than when the market is down (10.7%). The put long-short strategy is more profitable (18.1%) when the market is down than when the market is up (9.7%). This

[16]As discussed in Section 3.2, the accuracy of our cross-sectional forecast (as measured by $\overline{R}^2$) is *lower* when VIX is increasing. The long-short straddles portfolio, however, is still profitable because we *under*-predict the increase in volatility for decile ten.

result, however, is expected because the option prices move in accordance with the direction of the underlying asset. When VIX is considered as the reference state variable, we observe that call portfolio returns are negative when volatility increases while put portfolio returns are negative when volatility decreases. Again, this is to be expected because of the negative correlation between the VIX and the stock market. Market declines correspond to periods of increased volatility making call returns negative and put returns positive.

## 4.2 Stock Characteristics

Since options are derivative securities, it is reasonable to assume that option returns depend on the same sources of risks or characteristics that predict individual stock returns. The absence of a formal theoretical model for the cross-section of option returns further warrants considering stock factors related explanations for option returns. We, therefore, investigate how the long-short straddles portfolio returns are related to equity risk factors and characteristics. We consider two-way independent sorts – one based on volatility forecast and the second based on firm characteristics. The characteristics chosen are beta, size, book-to-market and past return. The first three of these are motivated by Fama and French (1992) while the last one is due to evidence of momentum profits by Jegadeesh and Titman (1993).[17] We sort stocks into quintile portfolios, as opposed to decile, to keep the portfolios well populated. Breakpoints for size, book-to-market, and momentum are based on only the stocks in our sample.

Table 7 shows the results of these double sorts. Panel A reports the results of double sorts based on volatility forecasts and stock beta. We find that there is no difference in returns of high beta stock straddles and those of low beta stock straddles across the first four of implied volatility quintiles. The difference in returns across implied volatility quintiles, however, is significant across all beta categories. There is also no clear pattern in long-short straddles returns across beta categories, although high beta stock straddles seem to generate the highest returns. Panel B shows that stock size does have an impact on straddles returns. The straddles returns for high implied volatility forecasts (quintile five) are higher for small stocks (11.6%) than those for large stocks (3.9%). Similarly, the straddles returns are significantly negative for low implied volatility forecasts (quintile one) only for small stocks (–10.2%). The difference in returns across implied volatility quintiles is highest for small stocks at 21.7% and decreases almost monotonically with

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

the increase in market capitalization of underlying stock. The largest two size quintiles have no statistically significant return difference between implied volatility quintile five and one. Panel C shows no clear evidence of relation between stock book-to-market and straddles returns. The difference in returns for implied volatility quintiles continues to be significant for both value (14.4%) and growth stocks (13.8%), albeit a bit higher for value stocks. Panel D reports the results of double sorts based on past return performance of stocks and implied volatility forecasts. There is no difference in returns between options on winner and loser stocks for the top two volatility quintiles. In implied volatility quintile one, options on loser stocks have more negative returns (–6.6%) than options on winner stocks (3.9%). In implied volatility quintile three, options on loser stocks have lower returns (0.5%) than options on winner stocks (5.5%). The difference in returns across implied volatility quintiles is highest for loser stocks at 15.1% and decreases almost monotonically with momentum.

Overall, the magnitude of the long-short straddles portfolio returns seems to be related to the firm characteristics: the average returns are higher for high beta, small market capitalization, and past loser stocks. However, the profits due to volatility predictability persist in any beta, size, book-to-market, and momentum portfolios indicating that the "volatility effect" is not subsumed by other effects typical of the cross-section of stock returns. The long-short straddles portfolio has statistically significant average returns that range from 2.7% to 21.7% per month.

Figure 1 shows that the equity option market was particularly active during the years of the "technology bubble." It is, therefore, imperative to establish if the volatility predictability is a phenomenon in only the technology industry. In unreported results, we find this not to be the case. The long-short straddles portfolio is quite profitable in each industry. The highest average return (9.4% per month) is in the finance sector while the lowest return (6.9%) is in the utilities industry. We also check if the distribution of industries is uniform across our deciles and find this to be the case.

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

## 4.3 Risk Adjusted Returns

We proceed by examining whether the profitability of the straddles portfolio is related to aggregate risk. We regress the long-short straddles portfolio return on various specifications of a linear pricing model composed by the Fama and French (1993) three factors model, the Carhart (1997) momentum factor, and changes in VIX. Option payoffs are non-linearly related to payoffs of stocks. Therefore, a linear factor model is unlikely to characterize the cross-section of option returns. We use a linear model merely to illustrate that the option returns described in this paper are not related to aggregate sources of risk in an obvious way. The use of changes in aggregate VIX is motivated by the fact that our option returns are the results of volatility mispricing that could be related to changes in aggregate risk. Moreover, Ang, Hodrick, Xing, and Xiaoyan (2006) find evidence for cross-sectional pricing of volatility risk for stocks.

Estimated parameters for these factor regressions are reported in Table 8. The first regression shows that the straddles portfolio has significant loadings on the standard Fama-French factors but not on the momentum factor. Moreover, the return of the straddles portfolio is negatively related to movements in the three stock market factors. The second specification shows that the loading on changes in VIX is positive and significant. The third regression shows that, when we consider all the factors together, only SMB, HML and $\Delta$ VIX have significant loadings. The $\overline{R}^2$ are relatively large, especially considering that we are analyzing a portfolio of options.

The return on the straddles portfolio is negatively related to movements in the three stock market factors.[18] This, therefore, does not suggest that the option returns are explainable in terms of remuneration for risk. To the contrary, the long-short strategy appears to be quite attractive because it also hedges the sources of aggregate risk that are priced in the stock market. The return on the straddles portfolio is also positively related to the changes in VIX. Since a volatility premium explanation would predict a negative loading on $\Delta$VIX, a positive loading implies that our strategy is a good hedge for volatility risk. This is also consistent with the evidence presented in Section 4.1, that shows higher long-short straddles returns in periods of increasing market volatility than in periods of decreasing volatility.

[18] As shown in Section 4.2, straddles returns are related to the characteristics of underlying stocks. However, this does not, by itself, imply that the loading of straddles returns on stock factors related to these characteristics will be significant. For instance, even though straddles returns are higher for smaller stocks than they are for larger stocks, this does not imply that the loading of *options* return on SMB *stock* factor should be positive.

## 4.4 Delta-Hedged Portfolios

We focus mostly on staddle portfolios in this paper because straddles portfolios seem naturally suited to exploit volatility predictability. However, another way to profit from better volatility forecasts is through delta hedging. In this approach, one constructs a delta-hedged call (put) portfolio by combining a call (put) and shorting (buying) delta shares of the underlying stock. Under appropriate assumptions (see for example Bakshi and Kapadia (2003) for a discussion of delta-hedged gains), this portfolio yields the risk-free rate with correct parameters and abnormal returns if implied volatility is mis-estimated. An advantage of this approach, relative to the straddles portfolio strategy, is potentially lower transaction costs since stock trading is cheaper than options trading. We turn to the issue of execution costs in the next section. The disadvantage is that straddles returns are more profitable than delta-hedged portfolios because the former benefit from volatility predictability of two options (call *and* put) while the latter benefit from volatility predictability of only one option (call *or* put).

We select options based on the same filters used in the rest of the paper. We use the delta (based on the current IV) provided to us by the IVY database. To take full advantage of volatility mispricing, a more powerful and profitable approach is to recalculate delta based on our implied volatility prediction. Figlewski (1989) notes that a delta-hedged strategy based on "incorrect" delta entails risk and does not provide a riskless rate of return. We, however, do not attempt to estimate a new delta because of computational difficulties (The deltas in the IVY database are calculated using a binomial tree model using Cox, Ross, and Rubinstein (1979)). This means that we are conservative in our construction of delta-hedged portfolios — we earn lower returns and have higher risk. Table 9 shows the returns on the delta-hedged calls (Panel A) and puts (Panel B).

The magnitude of returns in Table 9 is lower than that in Table 5. This is to be expected because the delta-hedged portfolios are riskless if implied volatility is correctly estimated. However, we still see that volatility predictability lends itself to positive returns for high decile portfolios and negative returns for low decile portfolios. Since these portfolios have low standard deviation, they have high SRs. For instance, SR for long-short call (put) delta-hedged portfolio is 0.923 (0.714). The absence of huge positive and negative returns also leads to positive CEs. Even with $\gamma = 7$, CE is 2.9% for calls and 1.5% for puts.

## 4.5 Trading Execution

There is a large body of literature documenting 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.[19] It is essential to understand to what degree these frictions prevent an investor from exploiting the profits on portfolio strategies studied in this paper. Therefore, in this section we discuss the impact of transaction costs, measured by the bid-ask spread and margin requirements, on the feasibility of the long-short strategy.

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 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. 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 in different liquidity groups. For each stock we compute the average quoted bid-ask spread and the daily average dollar volume in the previous month of all the option contracts traded on that stock. We then sort stocks based on these characteristics and calculate average returns and $t$-statistics for the long-short straddles portfolios for these groups of stocks. We report the results of these computations for straddles portfolios in Panel A of Table 10.

Portfolio returns decrease substantially, as expected, after taking transaction costs into account. The average returns of 15.0% to the long-short straddles portfolio are reduced to 5.3% when trading options at effective spreads that are half of quoted spreads. The liquidity of options also has an impact on returns as returns are higher for thinly

[19] 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).

traded stocks. Consider, as an illustration, the results for terciles (low, medium and high) obtained by sorting on the average bid-ask spread of options. The returns, computed from mid-points, to the long-short straddles portfolio are 12.4% for stocks with more liquid options (low bid-ask spreads) and 19.9% 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 insignificant for more liquid options and negative 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. If effective spreads are half as much as quoted spreads, the returns to the straddles portfolio are statistically significant at between 5.0% and 6.7% per month. The results are qualitatively the same when we sort stocks based on average daily trading volume of their options.

Section 4.4 alludes to the possibility that trading costs might be lower for delta-hedged portfolios than for straddles portfolios. This conjecture is investigated in detail in Panel B of Table 10. We consider the transaction costs of trading options only and assume that stocks trades can be executed without frictions. This is, obviously, a simplification (we do not have data on the trading costs of stocks). While this assumption surely biases our returns upwards, we do not believe that it is a serious omission for two reasons. One, stock trading costs are an order of magnitude smaller than those of stocks (Mayhew (2002)). Second, delta-hedged strategies that finish in-the-money require only half the spread to cover the positions at termination.[20] The pattern of higher returns for more liquid options is repeated in this panel. For instance, the returns on delta-hedged calls increase from 2.5% to 4.2% per month, and the returns on delta-hedged puts increase from 1.4% to 2.1% 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 half the quoted spreads, the delta-hedged calls have returns of around 2% while delta-hedged puts have returns of around 1%. Trading at quoted spreads eliminates profits to puts but calls are still profitable.

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 option market. However, margins on short positions have a smaller impact on trades that involve options with strike prices close to the money. The

[20]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).

short side of the long-short strategy involves options with high current IV and low (negative) expected change in IV. Therefore, these options have high prices and relatively high price-to-underlying ratios. Margin requirements for these options are relatively low and do not materially affect the execution of our strategies.

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

# 5 Discussion

IV from an option is the market's estimate of future volatility of the underlying asset. However, Section 3.4 shows that $\widehat{\text{IV}}$ is better than IV at predicting future realized volatility of the underlying stock. Since the option's value is related to the underlying future volatility over the life of the option, this provides the underlying economic rationale for the trading profits reported in the previous section.

One can view the implied volatility forecasts as being alternative estimates of option prices. A volatility forecast higher than the current IV implies an underpricing of the option (decile ten), and a volatility forecast lower than the current IV implies an overpricing of the option (decile one). In fact, when we reprice the options involved in the portfolio strategies by plugging the $\widehat{\text{IV}}$ estimate into the Black and Scholes (1973) model, the trading strategy is no longer profitable. For each of the decile groups obtained by sorting the out-of-sample volatility forecasts, we compute the portfolio returns using repriced options. We use the LIBOR rate as the interest rate, while the dividend yield is calculated from the last dividend paid by the firm. Untabulated results of this exercise show that the ten portfolio average returns are not statistically different from zero; the average return of decile one goes from –4.6% to an insignificant 4.7% while the return of decile ten goes from 15.0% to an insignificant 2.5%. Please note that, since the options are American, the Black and Scholes formula is obviously incorrect for pricing. However, our objective in this exercise is not to compute the "true" price of the option, rather it is to show that, on average, superior returns to portfolios are related only to implied volatility predictability. When we reprice the options, the returns are not statistically different from zero. The results, therefore, suggest that the modified price obtained from the volatility forecast is closer to the true price of the option.

As mentioned in the introduction, the market for equity options is active and presumably populated by sophisticated investors. It is, therefore, useful to consider why it might be the case that option implied volatilities are predictable. One reason may be that the 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 their volatility. This leads them to make inefficient predictions.

Our cross-sectional estimate, $\widehat{\mathrm{IV}}_{i,t\to t+1}$, is given by the combination of two different forecasts: one produced by the market and another computed using the cross-sectional forecasting model (2):

$$\widehat{\mathrm{IV}}_{i,t\to t+1} = \mathrm{IV}_{i,t} + \underbrace{\Delta\widehat{\mathrm{IV}}_{i,t\to t+1}}_{\text{shrinkage factor}} \tag{4}$$

Although we do not use any Bayesian techniques, $\Delta\widehat{\mathrm{IV}}_{i,t\to t+1}$ shares the shrinkage property with Stein's (1955) estimator.[21] It is negative for high values of $\mathrm{IV}_{i,t}$ and it is positive for low values of $\mathrm{IV}_{i,t}$ (Table 3). The average adjustment factor, $\Delta\widehat{\mathrm{IV}}_{i,t\to t+1}$, is equal to –8.0% (4.1%) for the decile with the lowest (highest) predicted change in IV. Since stocks in these deciles have, respectively, high (64.8%) and low (35.3%) current levels of IV, the adjustment factor effectively shrinks the tails of the distribution of IV towards the cross-sectional average. While in the classical Stein's estimator this property would be produced by explicitly operating on the cross-sectional average of IV, the informative prior, here we obtain it by filtering the data through the estimated parameters of a cross-sectional regression.

To offer more evidence, we plot $\Delta\widehat{\mathrm{IV}}_{i,t\to t+1}$ versus $\mathrm{IV}_{i,t}$ for September 2001 in Panel A of Figure 2. Similar to the results in Table 3, the figure shows that $\Delta\widehat{\mathrm{IV}}_{i,t\to t+1}$ tends to be negative for large values of $\mathrm{IV}_{i,t}$, while the reverse is true for small values of $\mathrm{IV}_{i,t}$. As a result the cross-sectional distribution of $\widehat{\mathrm{IV}}_{i,t\to t+1}$ is less dispersed than that of $\mathrm{IV}_{i,t}$ in most of the months in the sample. In Panel B of Figure 2 we plot the tails of the non-parametric kernel density of the cross-sectional distribution of $\mathrm{IV}_{i,t}$ (solid line) and $\widehat{\mathrm{IV}}_{i,t\to t+1}$ (dashed line). The left and right tails are plotted on the left and right sides of the figure. The left tail of $\widehat{\mathrm{IV}}_{i,t\to t+1}$ is towards the right of the left tail

[21] Shrinkage estimators of Stein (1955) improve the accuracy, defined as the expected square error, of an estimate by combining that estimate with some informative prior. The way the two estimates, the original and the prior, are combined is by shrinking towards the prior the estimates that are very far from it. Vasicek (1973) applies these methods to security betas (see also Blume (1971)) while Ledoit and Wolf (2003) present improved estimation of the variance covariance matrix using shrinkage techniques.

of $\mathrm{IV}_{i,t}$, while the opposite pattern is evident in the figure on the right. Our choice of this month is representative of the sample. Indeed, in about 82% of the months the left tail of the cross-sectional distribution of $\widehat{\mathrm{IV}}_{i,t\to t+1}$ lies to the right of the corresponding distribution of $\mathrm{IV}_{i,t}$. Similarly, in 92% of the months the right tail of $\widehat{\mathrm{IV}}_{i,t\to t+1}$ is to the left of the right tail of $\mathrm{IV}_{i,t}$. The range of $\widehat{\mathrm{IV}}_{i,t\to t+1}$, defined as the interval between the minimum and the maximum, lies within the range of the distribution of $\mathrm{IV}_{i,t}$ in 85% of the months. Moreover, the same range is on average 8.8% smaller than the range of the IV distribution.

Our evidence on implied volatility predictability is also broadly consistent with the findings of Stein (1989).[22] Stein studies the term structure of IV of index options and finds that investors overreact to the current information. They ignore the long run mean reversion in IV and instead overweight the current short-term IV in their estimates of long-term IV. This is analogous to our cross-sectional results, in which we find that stocks with low (high) current IV are the ones predicted to have the highest increase (decrease) in IV.

# 6 Conclusion

In this paper we document the existence of predictability in the cross-sectional distribution of equity option implied volatilities. We show that this predictability can be economically significant to investors. Various implications of the efficient market hypothesis in the context of options *pricing* have been examined in the prior literature. Our paper contributes to this by analyzing efficiency from the perspective of option *returns*, enabling us to explore the economic magnitude of the inefficiency uncovered in this paper.

The verdict about what generates this behavior on the part of the economic agents is left for future research. One possibility is that cross-sectional predictability stems from the fact that economic agents do not use all the available information in forming expectations about future stock volatilities. Although it is not clear whether the failure to incorporate cross-sectional information in implied volatility forecasts reflects behavioral biases, our evidence is also broadly consistent with the possibility that the investors overreact to current information.

[22] Poteshman (2001) also studies the term structure of various estimates of index IV. He arrives at the conclusion that inefficiencies exist but does not explore their economic magnitude.

# References


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

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

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

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

Ang, Andrew, Robert Hodrick, Yuhang Xing, and Zhing Xiaoyan, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 51, 259–299.

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

———, and Dilip Madam, 2003, Stock returns characteristics, skew laws, and the differential pricing of individual equity options, *Review of Financial Studies* 16, 101–143.

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

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

Battalio, Robert, and Paul Schultz, 2006, Options and the bubble, *Journal of Finance.*

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

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

Blume, Marshall E., 1971, On the assessment of risk, *Journal of Finance* 26, 1–10.

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

Canina, Linda, and Stephen Figlewski, 1993, The informational content of implied volatility, *Review of Financial Studies* 6, 659–681.

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

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

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

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

Das, Sanjiv Ranjan, and Rangarajan K. Sundaram, 1999, Of smiles and smirks: A term structure perspective, *Journal of Financial and Quantitative Analysis* 34, 211–239.

Day, Theodore E., and Craig M. Lewis, 1992, Stock market volatility and the information content of stock index options, *Journal of Econometrics* 52, 267–287.

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

Dennis, Patrick, and Stewart Mayhew, 2002, Risk-neutral skewness: Evidence from stock options, *Journal of Financial and Quantitative Analysis* 37, 471–493.

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

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

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

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

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

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

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

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

Fleming, Jeff, 1998, The quality of market volatility forecasts implied by S&P 100 index option prices, *Journal of Empirical Finance* 5, 317–345.

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

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

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

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

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

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

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

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

Lamoureux, Christopher G., and William D. Lastrapes, 1993, Forecasting stock-return variance: toward an understanding of stochastic implied volatilities, *Review of Financial Studies* 6, 293–326.

Ledoit, Olivier, and Michael Wolf, 2003, Improved estimation of the covariance matrix of stock returns with an application to portfolio selection, *Journal of Empirical Finance* 10, 603–621.

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

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

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

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

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

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

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

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

Stein, Charles, 1955, Inadmissibility of the usual estimator for the mean of a multivariate normal distribution, *Proceedings of the Third Berkeley Symposium* 1, 197–206.

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

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

Toft, Klaus Bjerre, and Brian Prucyk, 1997, Options on leverraged equity: Theory and empirical tests, *Journal of Finance* 52, 1151–1180.

Vasicek, Oldrich, 1973, A note on using cross-sectional information in bayesian estimation of security betas, *Journal of Finance* 28, 1233–1239.

**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 1996 to 2005.

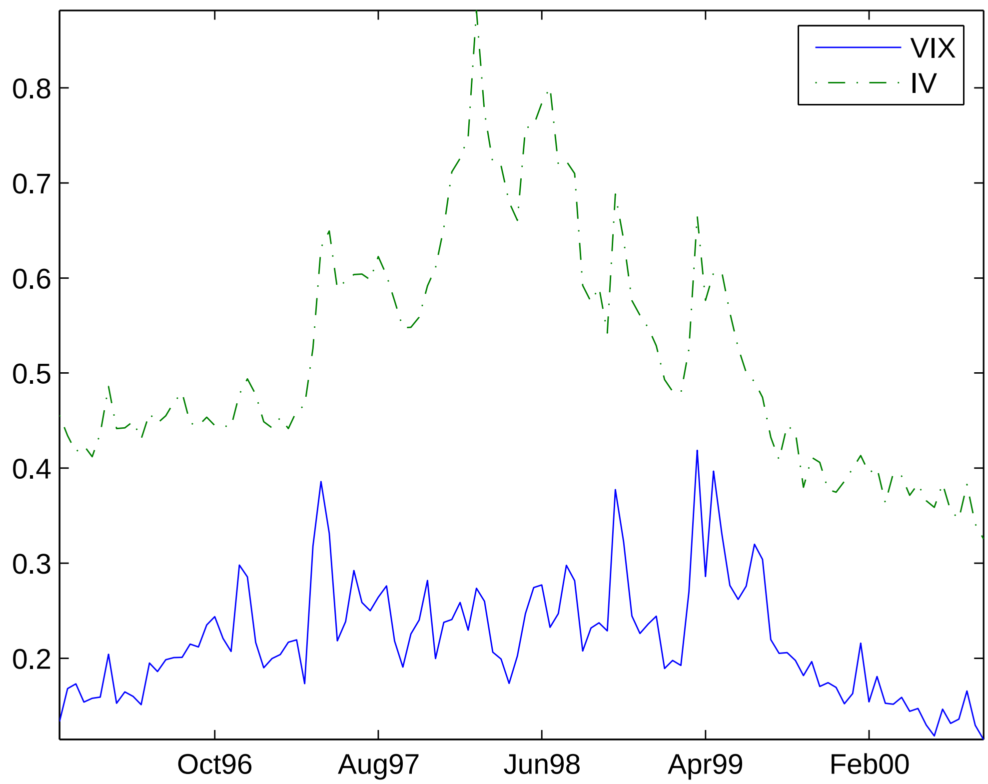
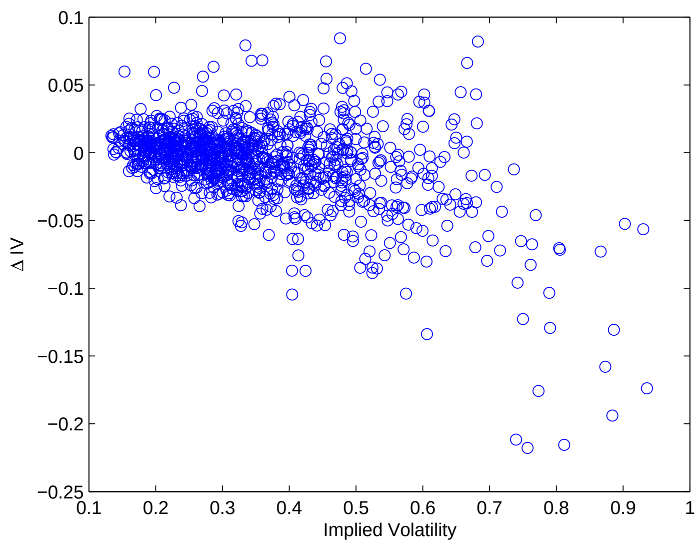


**Figure 2: Empirical Distribution of IV Forecast**

We select one call and one put for each stock in each month of the sample period. All options have expiration of one month and moneyness close to one. The IV for each stock is then the average of the IV of the selected call and put. All options are American. We estimate each month the forecasting model in equation (1). This gives us the estimate, $\widehat{\mathrm{IV}}_{i,t\to t+1}$, of the implied volatility on stock $i$ for month $t$. The market's estimate of implied volatility is given by $\mathrm{IV}_{i,t}$. In Panel A we plot $\Delta\widehat{\mathrm{IV}}_{i,t\to t+1}$ versus the $\mathrm{IV}_{i,t}$ for September 2001. In Panel B we plot the tails of the non-parametric kernel density of the cross-sectional distribution of $\mathrm{IV}_{i,t}$ (in solid line) and $\widehat{\mathrm{IV}}_{i,t\to t+1}$ (in dashed line).

**Panel A: Current and Predicted Change in Implied Volatility**




**Panel B: Empirical Distribution of Current and Predicted Implied Volatility**

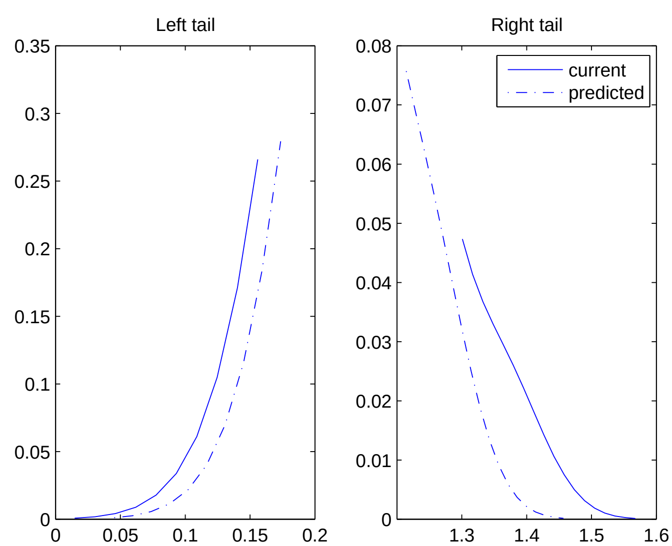


**Table 1: Summary Statistics**

This table reports summary statistics of the options used in this paper. We select one call and one put for each stock in each month of the sample period. All options have expirations of one month and moneyness close to one. We first compute the time-series average of these volatilities for each stock and then report the cross-sectional average of these average volatilities. The other statistics are computed in a similar fashion. We report statistics for the level and change of the ATM implied volatilities (IV), the smiles, and the level and change of the realized volatilities (RV). The IV for each stock is the average of the IV of the selected call and put. The smiles are computed as $SmL$ (the difference between 20% OTM put IV and ATM volatility) and $SmR$ (the difference between 20% OTM call IV and ATM volatility). The volatilities are in annualized basis. The sample period is from 1996 to 2005.

| | Mean | Median | StDev | Min | Max | Skew | Kurt |
|---|---|---|---|---|---|---|---|
| IV | 0.582 | 0.565 | 0.128 | 0.404 | 0.869 | 0.541 | 3.044 |
| $\Delta$IV | -0.006 | -0.010 | 0.152 | -0.280 | 0.302 | 0.178 | 3.190 |
| RV | 0.552 | 0.512 | 0.211 | 0.289 | 1.086 | 0.948 | 4.095 |
| $\Delta$ RV | 0.005 | 0.000 | 0.229 | -0.404 | 0.438 | 0.086 | 3.516 |
| $SmL$ | 0.074 | 0.056 | 0.079 | -0.038 | 0.260 | 0.752 | 3.467 |
| $SmR$ | 0.022 | 0.013 | 0.057 | -0.074 | 0.158 | 0.562 | 3.967 |

## Table 2: Volatility Predictability

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. We estimate each month the following forecasting model for the change in IV:

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

where $\mathrm{IV}_{i,t}$ is the ATM IV for stock $i$ measured in month $t$ and $\mathrm{RV}_{i,t}$ is the ATM IV for stock $i$ measured as the standard deviation of daily returns realized during month $t$. Lowercase letters denote natural logs ($iv = \log(\mathrm{IV})$ and $rv = \log(\mathrm{RV})$). The dependant variable is the change in IV, namely $\Delta iv_{i,t} = \log(\mathrm{IV}_{i,t}) - \log(\mathrm{IV}_{i,t-1})$. $\overline{iv}_{i,t-13:t-2}$ is the twelve months moving average of $iv_i$ and $\overline{rv}_{i,t-13:t-2}$ is the twelve months moving average of $rv_i$. The table reports the time-series averages of the estimates and Fama and MacBeth (1973) $t$-statistics adjusted for serial correlation in parenthesis below the coefficient. The row titled '$\overline{R}_t^2$' reports the time-series average and standard deviation (in curly brackets) of the $\overline{R}^2$ from cross-sectional regressions. The row titled '$\mathrm{RMSE}_i$' reports the cross-sectional average and standard deviation (in curly brackets) of the root mean square out-of-sample prediction errors (actual minus forecast). The row titled 'Nobs' reports the time-series average and standard deviation (in curly brackets) of the number of monthly observations. The sample period is from January 1996 to May 2005.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $iv_{t-1}$ | -0.084 | -0.043 | -0.068 | -0.050 |
| | (-12.43) | (-6.37) | (-10.01) | (-7.21) |
| $iv_{t-1} - \overline{iv}_{t-13:t-2}$ | | -0.323 | | -0.205 |
| | | (-33.26) | | (-26.05) |
| $iv_{t-1} - \overline{rv}_{t-13:t-2}$ | | | -0.259 | -0.142 |
| | | | (-21.95) | (-14.88) |
| $\overline{R}_t^2$ | 0.053 | 0.168 | 0.159 | 0.185 |
| | {0.05} | {0.06} | {0.07} | {0.07} |
| $\mathrm{RMSE}_i$ | 0.173 | 0.160 | 0.162 | 0.159 |
| | {0.08} | {0.07} | {0.07} | {0.07} |
| Nobs | 768 | 768 | 768 | 768 |
| | {129} | {129} | {129} | {129} |

## Table 3: Descriptive Statistics of Portfolios Sorted on Predicted Difference in Implied Volatility

We sort stocks into deciles based on implied volatility forecasts from Table 2. Decile ten is predicted to have the highest (positive) increase in implied volatility while decile one is predicted to have the lowest (negative) decrease in implied volatility. $\text{Mcap}_{i,t}$ is the market capitalization (in millions of dollars) of the underlying stock. $\text{IV}_{i,t}$ is the current IV of the stock (computed as the average of the implied volatilities extracted from the call and the put). $\text{IV}_{i,t} - \overline{\text{IV}}_t$ is the difference between the level of IV and the cross-sectional mean of IV. $\text{IV}_{i,t} - \overline{\text{IV}}_i$ is the difference between IV and the twelve months moving average of past IV. The last two rows report post-formation statistics. Specifically, $\Delta\widehat{\text{IV}}_{i,t\to t+1}$ is the out-of-sample predicted change and $\Delta\text{IV}_{i,t}$ is the actual change in IV. All statistics are first averaged across stocks in each decile. The table reports the monthly averages of these cross-sectional averages. Numbers in parenthesis are $t$-statistics. The sample period is from January 1996 to May 2005.

| Decile | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $\text{Mcap}_{i,t}$ | 4433.0 | 5542.9 | 6460.9 | 6970.9 | 7467.9 | 9272.0 | 9582.3 | 10647.7 | 11758.3 | 11021.4 |
| $\text{IV}_{i,t}$ | 0.683 | 0.587 | 0.543 | 0.511 | 0.485 | 0.459 | 0.438 | 0.417 | 0.394 | 0.361 |
| $\text{IV}_{i,t} - \overline{\text{IV}}_t$ | 0.115 | 0.062 | 0.034 | 0.012 | -0.005 | -0.024 | -0.039 | -0.052 | -0.068 | -0.085 |
| | (16.58) | (11.41) | (7.49) | (3.56) | (-1.82) | (-7.54) | (-13.06) | (-12.76) | (-11.90) | (-11.28) |
| $\text{IV}_{i,t} - \overline{\text{IV}}_i$ | 0.154 | 0.061 | 0.028 | 0.007 | -0.011 | -0.025 | -0.041 | -0.055 | -0.073 | -0.121 |
| | (15.58) | (8.18) | (4.22) | (1.10) | (-1.88) | (-4.42) | (-7.78) | (-10.32) | (-13.86) | (-21.78) |
| $\Delta\widehat{\text{IV}}_{i,t\to t+1}$ | -0.080 | -0.037 | -0.021 | -0.011 | -0.003 | 0.005 | 0.011 | 0.018 | 0.026 | 0.041 |
| | (-24.27) | (-12.93) | (-7.81) | (-3.97) | (-0.94) | (1.72) | (4.14) | (6.52) | (9.00) | (13.39) |
| $\Delta\text{IV}_{i,t+1}$ | -0.070 | -0.030 | -0.014 | -0.005 | -0.001 | 0.005 | 0.012 | 0.016 | 0.025 | 0.040 |
| | (-10.91) | (-5.93) | (-2.98) | (-1.04) | (-0.19) | (1.25) | (2.72) | (4.15) | (6.24) | (10.30) |

## Table 4: Forecasts of Future Realized Volatility

In this Table we report the estimation results of the following model for forecasting future realized volatility (RV):

$$RV_{t+1} = \alpha + \beta X_t + \epsilon_{t+1} \ .$$

The realized volatility is calculated using daily returns over the life of the option. The forecasting variables are the cross-sectional estimate ($\widehat{\text{IV}}_{t\to t+1}$) from Table 2, and the market $\text{IV}_t$. We run the regressions in two different ways. In Panel A, we report the results of a time series analysis wherein we run a forecasting regression for each stock; we tabulate the cross-sectional mean of the estimated coefficients and the standard deviation of the cross-sectional distribution in curly parenthesis. In Panel B, we tabulate results of a Fama-MacBeth regression in which we run a cross-sectional regression each month and tabulate the time-series average of the monthly coefficients along with $t$-statistics corrected for serial dependence in parenthesis. The sample period is from January 1996 to May 2005.

| | Const | $\widehat{\text{IV}}_{t\to t+1}$ | $\text{IV}_t$ | $\overline{R}^2$ |
|---|---|---|---|---|
| **Panel A: Time-series regression for each stock** | | | | |
| 1. | 0.161 | 0.626 | | 0.189 |
| | {0.25} | {0.45} | | |
| 2. | 0.178 | | 0.589 | 0.181 |
| | {0.29} | | {0.54} | |
| **Panel B: Cross-sectional regression across stocks** | | | | |
| 1. | 0.002 | 0.956 | | 0.498 |
| | (0.24) | (43.21) | | |
| 2. | 0.046 | | 0.846 | 0.469 |
| | (4.74) | | (36.01) | |

**Table 5: Portfolio Returns for Deciles Sorted on Implied Volatility Forecast**

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 (these are the same options that were used to generate the implied volatilities used in Table 2). We hold these options till expiration. 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. We sort stocks into deciles based on the implied volatility forecasts from Table 2. Decile ten is predicted to have the highest (positive) increase in implied volatility while decile one is predicted to have the lowest (negative) decrease in implied volatility. 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. Panel A reports returns for call portfolios, Panel B for put portfolios, Panel C for straddles (call and put) portfolios, and Panel D reports returns for underlying stock. The sample period is from January 1996 to May 2005.

| Decile | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10–1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Panel A: Call returns | | | | | | |
| mean | -0.046 | 0.006 | 0.047 | 0.070 | 0.082 | 0.077 | 0.067 | 0.086 | 0.118 | 0.210 | 0.256 |
| std | 0.543 | 0.549 | 0.578 | 0.587 | 0.615 | 0.611 | 0.630 | 0.656 | 0.697 | 0.828 | 0.589 |
| min | -0.880 | -0.972 | -0.948 | -0.986 | -0.950 | -0.973 | -0.979 | -0.949 | -0.992 | -0.976 | -0.698 |
| max | 1.845 | 1.558 | 1.708 | 1.661 | 1.710 | 2.196 | 1.704 | 2.233 | 2.879 | 4.908 | 4.711 |
| SR | -0.091 | 0.006 | 0.076 | 0.114 | 0.129 | 0.121 | 0.102 | 0.127 | 0.165 | 0.250 | 0.435 |
| CE ($\gamma = 3$) | -0.571 | -0.757 | -0.614 | -0.861 | -0.654 | -0.757 | -0.813 | -0.647 | -0.921 | -0.780 | -0.067 |
| CE ($\gamma = 7$) | -0.783 | -0.939 | -0.886 | -0.969 | -0.891 | -0.942 | -0.953 | -0.889 | -0.983 | -0.948 | -0.449 |
| | | | | | Panel B: Put returns | | | | | | |
| mean | -0.010 | -0.048 | -0.063 | -0.049 | -0.015 | -0.028 | -0.027 | -0.006 | -0.017 | 0.057 | 0.067 |
| std | 0.624 | 0.649 | 0.602 | 0.634 | 0.684 | 0.658 | 0.700 | 0.750 | 0.688 | 0.801 | 0.502 |
| min | -0.926 | -0.802 | -0.856 | -0.832 | -0.868 | -0.859 | -0.912 | -0.897 | -0.891 | -0.857 | -1.683 |
| max | 2.387 | 2.510 | 2.454 | 2.722 | 2.720 | 3.178 | 3.377 | 3.534 | 3.215 | 4.031 | 1.866 |
| SR | -0.020 | -0.079 | -0.110 | -0.083 | -0.027 | -0.047 | -0.043 | -0.012 | -0.029 | 0.068 | 0.134 |
| CE ($\gamma = 3$) | -0.525 | -0.497 | -0.512 | -0.481 | -0.516 | -0.507 | -0.557 | -0.573 | -0.532 | -0.492 | -0.834 |
| CE ($\gamma = 7$) | -0.837 | -0.663 | -0.726 | -0.680 | -0.743 | -0.719 | -0.812 | -0.799 | -0.774 | -0.717 | -0.955 |

| Decile | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10–1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel C: straddles returns | | | | | | | | | | | |
| mean | -0.046 | -0.031 | -0.011 | 0.003 | 0.022 | 0.004 | 0.018 | 0.032 | 0.050 | 0.103 | 0.150 |
| std | 0.179 | 0.183 | 0.192 | 0.207 | 0.216 | 0.218 | 0.238 | 0.247 | 0.248 | 0.281 | 0.239 |
| min | -0.355 | -0.341 | -0.338 | -0.344 | -0.405 | -0.363 | -0.333 | -0.387 | -0.361 | -0.353 | -0.413 |
| max | 0.617 | 0.729 | 0.834 | 0.805 | 1.008 | 0.973 | 1.318 | 1.361 | 1.297 | 1.421 | 1.250 |
| SR | -0.276 | -0.186 | -0.075 | -0.000 | 0.088 | 0.003 | 0.064 | 0.120 | 0.188 | 0.356 | 0.626 |
| CE ($\gamma = 3$) | -0.090 | -0.075 | -0.059 | -0.048 | -0.033 | -0.051 | -0.039 | -0.031 | -0.012 | 0.025 | 0.080 |
| CE ($\gamma = 7$) | -0.137 | -0.120 | -0.112 | -0.098 | -0.098 | -0.106 | -0.092 | -0.095 | -0.072 | -0.050 | -0.023 |
| Panel D: Stock returns | | | | | | | | | | | |
| mean | 0.014 | 0.015 | 0.016 | 0.013 | 0.012 | 0.012 | 0.009 | 0.008 | 0.009 | 0.005 | -0.009 |
| std | 0.078 | 0.072 | 0.067 | 0.068 | 0.067 | 0.061 | 0.061 | 0.060 | 0.058 | 0.057 | 0.042 |
| min | -0.206 | -0.224 | -0.194 | -0.222 | -0.241 | -0.206 | -0.238 | -0.224 | -0.193 | -0.202 | -0.141 |
| max | 0.183 | 0.161 | 0.170 | 0.165 | 0.174 | 0.166 | 0.155 | 0.133 | 0.150 | 0.141 | 0.083 |
| SR | 0.148 | 0.168 | 0.191 | 0.155 | 0.128 | 0.153 | 0.093 | 0.076 | 0.101 | 0.039 | -0.220 |
| CE ($\gamma = 3$) | 0.005 | 0.007 | 0.009 | 0.006 | 0.004 | 0.006 | 0.003 | 0.002 | 0.004 | 0.000 | -0.012 |
| CE ($\gamma = 7$) | -0.008 | -0.005 | -0.001 | -0.005 | -0.007 | -0.003 | -0.007 | -0.007 | -0.004 | -0.008 | -0.016 |

## Table 6: Straddles Portfolio Returns in Subsamples

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 (these are the same options that were used to generate the implied volatilities used in Table 2). We hold these options till expiration. 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. We sort stocks into deciles based on the implied volatility forecasts from Table 2. Decile ten is predicted to have the highest (positive) increase in implied volatility while decile one is predicted to have the lowest (negative) decrease in implied volatility. 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 on the straddles portfolios. We separate the sample period into two states based on the market returns in Panel A and the market volatility in Panel B. The market return is proxied by the value-weighted return on CRSP market portfolio while market volatility is measured by VIX. The first row gives the average return while the second row gives the $t$-statistics of the return in parenthesis. The sample period is from January 1996 to May 2005.

| Volatility Decile | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10–1 |
| Panel A: Based on market volatility | | | | | | | | | | |
| Up volatility | | | | | | | | | | |
| -0.048 | -0.009 | 0.018 | 0.028 | 0.073 | 0.035 | 0.081 | 0.122 | 0.138 | 0.220 | 0.268 |
| (-1.56) | (-0.25) | (0.51) | (0.73) | (1.71) | (0.90) | (1.67) | (2.53) | (2.86) | (4.22) | (7.32) |
| Down volatility | | | | | | | | | | |
| -0.046 | -0.050 | -0.032 | -0.017 | -0.010 | -0.013 | -0.023 | -0.016 | -0.000 | 0.040 | 0.085 |
| (-2.22) | (-2.82) | (-1.49) | (-0.79) | (-0.47) | (-0.54) | (-1.05) | (-0.72) | (-0.01) | (1.48) | (3.31) |
| Up – Down | | | | | | | | | | |
| -0.002 | 0.042 | 0.049 | 0.045 | 0.083 | 0.048 | 0.103 | 0.139 | 0.138 | 0.180 | 0.182 |
| (-0.05) | (1.05) | (1.22) | (1.02) | (1.75) | (1.05) | (1.95) | (2.60) | (2.58) | (3.07) | (4.07) |
| Panel B: Based on market returns | | | | | | | | | | |
| Up market | | | | | | | | | | |
| -0.028 | -0.031 | 0.002 | 0.010 | 0.013 | 0.012 | 0.007 | 0.013 | 0.018 | 0.063 | 0.091 |
| (-1.38) | (-1.55) | (0.10) | (0.47) | (0.65) | (0.49) | (0.34) | (0.61) | (0.76) | (2.31) | (3.46) |
| Down market | | | | | | | | | | |
| -0.068 | -0.027 | -0.032 | -0.007 | 0.036 | -0.005 | 0.030 | 0.062 | 0.096 | 0.160 | 0.228 |
| (-2.33) | (-0.88) | (-0.95) | (-0.20) | (0.87) | (-0.14) | (0.65) | (1.30) | (2.12) | (3.15) | (6.03) |
| Up – Down | | | | | | | | | | |
| 0.040 | -0.004 | 0.034 | 0.018 | -0.023 | 0.017 | -0.022 | -0.050 | -0.078 | -0.097 | -0.137 |
| (1.13) | (-0.11) | (0.86) | (0.42) | (-0.50) | (0.38) | (-0.44) | (-0.95) | (-1.52) | (-1.68) | (-2.97) |

**Table 7: Straddles Returns by Volatility Forecast and Stock Characteristics**

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 (these are the same options that were used to generate the implied volatilities used in Table 2). We hold these options till expiration. 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. We sort stocks independently into quintiles based on the implied volatility forecasts from Table 2 and into quintiles based on stock characteristics. For volatility sorts, quintile 1 consists of stocks predicted to have the lowest (negative) decrease in implied volatility while quintile 5 consists of stocks predicted to have the highest (positive) increase in implied volatility. We consider four stock characteristics, namely beta (Panel A), market size (Panel B), book-to-market ratio (Panel C), and momentum (Panel D). Breakpoints for these stock characteristics are calculated each month based only on stocks in our sample. The monthly returns on options are averaged across all the stocks in any sub-group. The table then reports the average return and the associated $t$-statistic of this continuous time-series of monthly returns on the straddles in each of the $5 \times 5$ sub-groups. The sample period is from January 1996 to May 2005.

| | Volatility Quintile | | | | | | Volatility Quintile | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 5–1 | 1 | 2 | 3 | 4 | 5 | 5–1 |
| **Panel A: Based on stock beta** | | | | | | | | | | | | |
| | Mean | | | | | | $t$-statistic | | | | | |
| L=1 | -0.066 | -0.046 | 0.038 | -0.017 | 0.033 | 0.099 | -2.98 | -1.93 | 1.50 | -0.69 | 1.17 | 3.47 |
| 2 | -0.032 | -0.009 | -0.013 | 0.024 | 0.056 | 0.088 | -1.39 | -0.39 | -0.57 | 0.89 | 2.10 | 3.75 |
| 3 | 0.002 | 0.018 | -0.001 | 0.022 | 0.082 | 0.080 | 0.09 | 0.77 | -0.04 | 0.75 | 2.93 | 3.14 |
| 4 | -0.030 | 0.018 | 0.027 | 0.049 | 0.091 | 0.121 | -1.28 | 0.72 | 1.08 | 1.78 | 3.17 | 4.26 |
| H=5 | -0.054 | -0.016 | 0.011 | 0.013 | 0.134 | 0.187 | -2.34 | -0.57 | 0.38 | 0.43 | 3.76 | 6.26 |
| H–L | 0.012 | 0.030 | -0.027 | 0.030 | 0.101 | | 0.42 | 0.94 | -0.92 | 1.02 | 3.26 | |
| **Panel B: Based on stock market capitalization** | | | | | | | | | | | | |
| | Mean | | | | | | $t$-statistic | | | | | |
| S=1 | -0.102 | -0.040 | -0.011 | 0.006 | 0.116 | 0.217 | -6.05 | -2.07 | -0.51 | 0.27 | 4.31 | 10.46 |
| 2 | -0.032 | 0.003 | 0.020 | 0.034 | 0.095 | 0.127 | -1.83 | 0.17 | 0.97 | 1.48 | 3.56 | 5.37 |
| 3 | -0.032 | -0.032 | 0.019 | 0.022 | 0.099 | 0.132 | -1.55 | -1.60 | 0.87 | 0.84 | 3.71 | 4.91 |
| 4 | 0.025 | 0.018 | 0.015 | 0.029 | 0.072 | 0.048 | 0.99 | 0.73 | 0.64 | 1.13 | 2.56 | 1.58 |
| B=5 | 0.013 | 0.032 | 0.016 | 0.022 | 0.039 | 0.027 | 0.44 | 1.18 | 0.56 | 0.75 | 1.18 | 0.73 |
| S–B | -0.114 | -0.072 | -0.027 | -0.017 | 0.076 | | -4.00 | -2.80 | -1.09 | -0.66 | 2.46 | |

| | Volatility Quintile | | | | | | Volatility Quintile | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 5–1 | 1 | 2 | 3 | 4 | 5 | 5–1 |
| **Panel C: Based on stock book-to-market** | | | | | | | | | | | | |
| | Mean | | | | | | $t$-statistic | | | | | |
| L=1 | -0.041 | 0.018 | 0.041 | 0.030 | 0.097 | 0.138 | -2.07 | 0.78 | 1.78 | 1.14 | 2.75 | 4.67 |
| 2 | -0.025 | 0.008 | 0.035 | 0.006 | 0.076 | 0.100 | -1.15 | 0.37 | 1.44 | 0.26 | 2.86 | 3.87 |
| 3 | -0.037 | -0.030 | -0.005 | 0.030 | 0.090 | 0.127 | -1.72 | -1.41 | -0.23 | 1.08 | 3.01 | 4.58 |
| 4 | -0.058 | -0.009 | -0.004 | 0.040 | 0.065 | 0.123 | -2.60 | -0.36 | -0.17 | 1.38 | 2.30 | 4.70 |
| H=5 | -0.067 | -0.039 | -0.029 | 0.028 | 0.077 | 0.144 | -2.95 | -1.44 | -1.06 | 0.99 | 2.46 | 5.09 |
| H–L | -0.026 | -0.057 | -0.071 | -0.002 | -0.020 | | -0.94 | -2.05 | -2.45 | -0.06 | -0.53 | |
| **Panel D: Based on stock momentum** | | | | | | | | | | | | |
| | Mean | | | | | | $t$-statistic | | | | | |
| L=1 | -0.066 | -0.015 | 0.005 | 0.045 | 0.085 | 0.151 | -3.99 | -0.73 | 0.23 | 2.00 | 2.77 | 5.98 |
| 2 | -0.083 | -0.043 | -0.011 | 0.014 | 0.048 | 0.131 | -4.14 | -2.03 | -0.47 | 0.57 | 1.84 | 5.32 |
| 3 | -0.073 | -0.044 | 0.005 | 0.003 | 0.059 | 0.132 | -3.67 | -1.91 | 0.22 | 0.11 | 2.19 | 5.37 |
| 4 | -0.040 | -0.004 | -0.000 | 0.021 | 0.066 | 0.106 | -1.79 | -0.18 | -0.00 | 0.84 | 2.48 | 3.99 |
| W=5 | 0.039 | 0.049 | 0.055 | 0.052 | 0.122 | 0.083 | 1.62 | 1.92 | 2.28 | 1.89 | 4.13 | 2.99 |
| W–L | 0.105 | 0.064 | 0.050 | 0.007 | 0.037 | | 4.38 | 2.54 | 2.07 | 0.30 | 1.25 | |

## Table 8: Risk-Adjusted Straddles Returns

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 (these are the same options that were used to generate the implied volatilities used in Table 2). We hold these options till expiration. 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. We sort stocks into deciles based on the implied volatility forecasts from Table 2. Decile ten is predicted to have the highest (positive) increase in implied volatility while decile one is predicted to have the lowest (negative) decrease in implied volatility. The monthly returns on options are averaged across all the stocks in the volatility decile. We then regress the 10–1 straddles portfolio returns on risk factors. We consider risk factors from the Fama and French (1993) three-factor model, the Carhart (1997) momentum factor, and changes in VIX. The first row gives the coefficient while the second row gives the *t*-statistics in parenthesis. The sample period is from January 1996 to May 2005.

| | (1) | (2) | (3) |
|---|---|---|---|
| Const | 0.132 | 0.120 | 0.131 |
| | (10.17) | (8.93) | (10.88) |
| MKT | -0.672 | | -0.318 |
| | (-2.42) | | (-1.15) |
| SMB | -1.468 | | -1.400 |
| | (-5.01) | | (-4.88) |
| HML | -1.339 | | -1.351 |
| | (-3.61) | | (-3.76) |
| MOM | 0.273 | | 0.195 |
| | (1.37) | | (0.88) |
| $\Delta$VIX | | 0.994 | 0.905 |
| | | (3.03) | (3.52) |
| $\overline{R}^2$ | 0.217 | 0.093 | 0.270 |

## Table 9: Delta-Hedged Portfolio Returns

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 (these are the same options that were used to generate the implied volatilities used in Table 2). We hold these options till expiration. 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. We sort stocks into deciles based on the implied volatility forecasts from Table 2. Decile ten is predicted to have the highest (positive) increase in implied volatility while decile one is predicted to have the lowest (negative) decrease in implied volatility. The monthly returns on delta-hedged portfolios are averaged across all the stocks in the volatility decile. Panel A considers returns on delta-hedged call portfolios while Panel B considers returns on delta-hedged put portfolios. 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 from January 1996 to May 2005.

| Decile | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10–1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Call-Hedged returns | | | | | | | | | | | |
| mean | -0.023 | -0.015 | -0.011 | -0.008 | -0.006 | 0.001 | -0.003 | -0.003 | 0.002 | 0.009 | 0.033 |
| std | 0.040 | 0.036 | 0.033 | 0.033 | 0.040 | 0.054 | 0.034 | 0.048 | 0.031 | 0.029 | 0.035 |
| min | -0.204 | -0.135 | -0.126 | -0.134 | -0.190 | -0.063 | -0.126 | -0.394 | -0.153 | -0.044 | -0.015 |
| max | 0.112 | 0.132 | 0.134 | 0.123 | 0.163 | 0.473 | 0.170 | 0.165 | 0.131 | 0.146 | 0.203 |
| SR | -0.665 | -0.489 | -0.430 | -0.321 | -0.219 | -0.037 | -0.179 | -0.116 | -0.041 | 0.216 | 0.923 |
| CE ($\gamma = 3$) | -0.026 | -0.017 | -0.013 | -0.009 | -0.008 | -0.002 | -0.005 | -0.008 | 0.000 | 0.008 | 0.031 |
| CE ($\gamma = 7$) | -0.030 | -0.019 | -0.015 | -0.011 | -0.012 | -0.005 | -0.007 | -0.028 | -0.002 | 0.007 | 0.029 |
| Panel B: Put-Hedged returns | | | | | | | | | | | |
| mean | -0.008 | -0.003 | -0.001 | -0.000 | 0.002 | 0.002 | 0.002 | 0.004 | 0.005 | 0.009 | 0.017 |
| std | 0.030 | 0.027 | 0.027 | 0.026 | 0.026 | 0.026 | 0.025 | 0.025 | 0.022 | 0.024 | 0.023 |
| min | -0.093 | -0.068 | -0.063 | -0.052 | -0.051 | -0.055 | -0.045 | -0.040 | -0.040 | -0.042 | -0.052 |
| max | 0.097 | 0.097 | 0.107 | 0.107 | 0.117 | 0.130 | 0.132 | 0.129 | 0.095 | 0.125 | 0.116 |
| SR | -0.359 | -0.238 | -0.157 | -0.123 | -0.018 | -0.023 | -0.028 | 0.024 | 0.101 | 0.245 | 0.714 |
| CE ($\gamma = 3$) | -0.009 | -0.004 | -0.002 | -0.001 | 0.002 | 0.001 | 0.001 | 0.003 | 0.004 | 0.008 | 0.016 |
| CE ($\gamma = 7$) | -0.011 | -0.006 | -0.004 | -0.002 | 0.000 | 0.000 | 0.000 | 0.002 | 0.004 | 0.007 | 0.015 |

## Table 10: Impact of Liquidity and Transaction Costs

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 (these are the same options that were used to generate the implied volatilities used in Table 2). We hold these options till expiration. 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. We sort stocks independently into deciles based on based on the implied volatility forecasts from Table 2 and into terciles based on stock options' liquidity characteristics. For volatility sorts, decile ten is predicted to have the highest (positive) increase in implied volatility while decile one is predicted to have the lowest (negative) decrease in implied volatility. For stock options liquidity sorts, we consider groups based on the average quoted bid-ask spread of all the options series traded in the previous month, as well as groups based on daily average dollar volume of all the options series traded in the previous month. The monthly returns on options (or delta-hedged portfolios) are averaged across all the stocks in any particular sub-group. Panel A considers returns on long-short 10–1 straddles portfolio while Panel B considers returns on long-short 10–1 delta-hedged calls/puts. The table then reports the average return and 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 from January 1996 to May 2005.

Panel A: Returns on 10–1 straddles portfolios

| | | ESPR/QSPR | | |
|---|---|---|---|---|
| | MidP | 50% | 75% | 100% |
| All | 0.150 | 0.053 | 0.005 | -0.044 |
| | (6.57) | (2.42) | (0.23) | (-2.04) |
| **Based on average bid-ask spread of options** | | | | |
| Low | 0.124 | 0.067 | 0.041 | 0.016 |
| | (3.75) | (2.10) | (1.29) | (0.49) |
| Medium | 0.140 | 0.050 | 0.008 | -0.035 |
| | (4.66) | (1.72) | (0.28) | (-1.17) |
| High | 0.199 | 0.066 | 0.003 | -0.064 |
| | (6.80) | (2.37) | (0.11) | (-2.26) |
| **Based on average trading volume of options** | | | | |
| Low | 0.186 | 0.071 | 0.014 | -0.044 |
| | (6.39) | (2.52) | (0.50) | (-1.57) |
| Medium | 0.152 | 0.064 | 0.021 | -0.024 |
| | (5.01) | (2.17) | (0.70) | (-0.81) |
| High | 0.110 | 0.048 | 0.017 | -0.013 |
| | (3.41) | (1.51) | (0.55) | (-0.42) |

| 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% |
| Based on average bid-ask spread of options | | | | | | | | |
| Low | 0.025 | 0.018 | 0.014 | 0.011 | 0.014 | 0.008 | 0.005 | 0.003 |
| | (5.77) | (4.05) | (3.24) | (2.48) | (3.84) | (2.28) | (1.53) | (0.79) |
| Medium | 0.028 | 0.016 | 0.011 | 0.006 | 0.015 | 0.006 | 0.001 | -0.003 |
| | (6.66) | (4.23) | (2.99) | (1.72) | (4.57) | (1.81) | (0.46) | (-0.91) |
| High | 0.042 | 0.024 | 0.016 | 0.008 | 0.021 | 0.007 | 0.001 | -0.006 |
| | (6.40) | (5.33) | (3.96) | (2.27) | (7.44) | (2.60) | (0.20) | (-2.27) |
| Based on average trading volume of stock options | | | | | | | | |
| Low | 0.034 | 0.021 | 0.014 | 0.007 | 0.022 | 0.010 | 0.004 | -0.002 |
| | (10.81) | (6.73) | (4.56) | (2.32) | (8.17) | (3.72) | (1.41) | (-0.92) |
| Medium | 0.035 | 0.022 | 0.017 | 0.011 | 0.018 | 0.009 | 0.004 | -0.001 |
| | (4.71) | (4.15) | (3.37) | (2.39) | (5.68) | (2.79) | (1.31) | (-0.17) |
| High | 0.022 | 0.015 | 0.011 | 0.007 | 0.008 | 0.002 | -0.000 | -0.003 |
| | (5.37) | (3.65) | (2.72) | (1.78) | (2.35) | (0.70) | (-0.14) | (-0.97) |