The Joint Cross Section of Stocks and Options*

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ABSTRACT

Option volatilities have significant predictive power for the cross section of stock returns and vice versa. Stocks with large increases in call implied volatilities tend to rise over the following month and increases in put implied volatilities forecast future decreases in next-month stock returns. The spread in average returns and alphas between the first and fifth quintile portfolios formed by ranking on lagged changes in implied call volatilities is approximately 1% per month. Going in the other direction, stocks with high returns over the past month tend to have call option contracts that exhibit increases in implied volatility over the next month, but realized volatility for those stocks tends to decrease.

1. Introduction

Options are redundant assets only in an idealized world of complete markets with no transactions costs, perfect information, and no restrictions on shorting. Not surprisingly, since in the real world none of these assumptions hold, options are not spanned by stock prices and option prices are not merely functions of underlying stock prices and risk-free securities. Many theoretical models jointly pricing options and underlying assets in incomplete markets have incorporated many of these real-world frictions.[1] In addition, if informed traders tend to choose certain markets over others, information-based models such as Easley, O'Hara and Srinivas (1998) predict that those markets where informed trading takes place will lead other markets where informed trading does not predominate.

Option markets have significant advantages for informed traders as enumerated by Black (1975), Grossman (1977), Diamond and Verrechia (1987), and others. Options offer an alternative way to take short positions when short positions in the underlying asset would be prohibitively expensive. Options provide additional leverage which may not be possible, or relatively expensive, to obtain in stock and bond markets (see Back, 1993; Biais and Hillion, 1994). Options also reduce transactions costs of making replicating trades in the underlying stocks. On the other hand, an informed trader may not always first choose to trade in options markets over underlying equity markets. Option trading volumes are much lower than trading volumes in the underlying stocks, which make hiding informed trades harder in option markets. As Easley, O'Hara and Srinivas (1998) show, only when the implicit leverage available in options is large and the option market offers sufficient liquidity will informed investors first trade in option markets. Conversely, if informed traders can more easily hide in equity markets, then equity returns will lead option prices.

We document that the cross section of option volatilities contains information that forecasts the cross section of expected stock returns. Stocks with call options that have experienced increases in implied volatilities over the past month tend to experience high expected returns over the next month. Increases in put option volatilities predict decreases in next-month stock returns. While strongest for the next-month horizon, this predictability persists for several months. The strength and persistence of this predictability is remarkable. First, the innovation in implied volatilities can be considered to be a very simple measure of news arrivals in the option market. The predictability at the standard monthly horizon suggests the predictability is unlikely due to microstructure trading effects. In contrast, most of the

[1] See Detemple and Selden (1991), Back (1993), Cao (1999), Buraschi and Jiltsov (2006), and Vanden (2008), among others.

previous literature investigating lead-lag effects of options versus stock markets focuses on intra-day or daily frequencies.

The predictability is statistically very strong and economically large. Quintile portfolios formed on past changes in call option volatility have a spread of approximately 1% per month in both raw returns and alphas computed using common systematic factor models. The difference between the top and bottom quintile portfolios in ranking stocks by past changes in put implied volatilities is approximately 60 basis points per month after controlling for the effect of call volatility innovations. The predictability of stock returns by option innovations is also robust in several subsamples. Whereas many cross-sectional strategies have reversed sign or become much weaker during the recent financial crisis, the ability of option volatilities to predict returns is still seen in very recent data. In particular, the predictive relation between large put volatility innovations and future low stock returns is very prominent in 2008.

Although calls and puts contain different information, a consistent story for this predictability is that option prices change due to the action of informed investors, and this information is not contemporaneously reflected in equity markets. Thus, at least some informed traders are moving first in option markets. Bullish investors first trading in option markets could either buy call options or equivalently sell put options, and both higher call volatilities and lower put volatilities lead future increases in stock returns. Consistent with the actions of informed investors, the predictability of implied option volatility changes is strongest when they are accompanied by large contemporaneous changes in option volume. In addition, we find that the economic source of the return predictability by option innovations is almost all due to changes in idiosyncratic, not systematic, components of implied volatilities. This is consistent with the investors first trading option markets having better information about company-specific events or news.

We also uncover evidence of reverse directional predictability from stock variables to option markets. Many of the variables long known to predict stock returns also predict option implied volatilities. A very simple predictor is the past return of a stock: stocks with high past returns over the previous month tend to have call options that exhibit increases in volatility over the next month. In particular, stocks with abnormal returns of 1% relative to the CAPM tend to see call implied volatilities increase over the next month by approximately 2%. There are no corresponding increases in realized stock volatilities over the next month. This predictability also persists for several months. The predictability of lagged stock returns and other stock characteristics for future changes in option implied volatilities is in addition to the well-known documented predictability of option market returns by option market variables.[2] Behavioral over-reaction models of option mispricing predict that option implied volatilities should increase together with other measures of uncertainty such as earnings dispersion. We find this is not the case. The cross-sectional predictability of option volatilities is stronger in stocks which exhibit a lower degree of return predictability and options which are harder to hedge, consistent with rational stories on option volatility predictability.

2. Related Literature

We follow an older literature that debates whether options or stocks lead or lag each other. These earlier studies are all conducted at the daily or intra-day frequencies. Manaster and Rendleman (1982), Bhattacharya (1987), and Anthony (1988) find that options predict future stock prices. Fleming, Ostdiek and Whaley (1996) document derivatives lead the underlying markets using futures and options on futures. On the other hand, Stephan and Whaley (1990) and Chan, Chung and Johnson (1993) find stock markets lead option markets. Chakravarty, Gulen and Mayhew (2004) find that both stock and option markets contribute to price discovery. Our findings are very different from this literature because we find that option volatility innovations contain strong predictive power for the cross section of equity returns at the much lower monthly frequency. Similarly, we find predictability of stock characteristics, including past one-month stock returns, for future implied volatilities at the monthly frequency.

The joint predictability of the cross section of option implied volatilities on stock returns and vice versa indicates that both options and underlying equities play an important role in the price formation of each other's markets. Our empirical findings are partly consistent with the model of Easley, O'Hara and Srinivas (1998) where informed traders place orders in the equity market, the options market, or both. If at least some informed investors choose to trade in options before trading in underlying stocks, then some option prices will predict future stock price movements. Conversely, if stock markets are more liquid and informed traders can more easily hide their trades in equities, then stock markets may lead option markets. Easley, O'Hara and Srinivas find evidence that option volumes of certain types of trades forecast future stock prices within the next hour using intraday data, consistent with price updating occurring according to a microstructure model. The monthly frequency predictability we find, however, is probably not due to microstructure frictions.

Our findings are related to a more recent literature showing that option prices contain predictive information about stock returns. Cao, Chen and Griffin (2005) find that merger information hits the call

[2] Obviously this predictability overwhelmingly rejects arbitrage-free option pricing models, which a long literature has also shown. The earlier papers in this literature include Figlewski (1989) and Longstaff (1995). More recently see Cao and Han (2009) and Goyal and Saretto (2009).

option market prior to the stock market, but focus only on these special corporate events. More recent studies such as Bali and Hovakimian (2009), Cremers and Weinbaum (2010), and Xing, Zhang, and Zhao (2010) use information in the cross section of options including the difference between implied and realized volatilities, put-call parity deviations, and risk-neutral skewness. Our option volatility innovation measures are simpler, and the predictive ability of changes in implied volatilities is different to option market information used by previous authors. We relate changes in option volatilities to contemporaneous changes in option volume, indicating that that informed trading is likely taking place in option markets and moving option prices before being captured in stock markets.

Other related studies focus on predicting option returns, option trading volume, or the option skew in the cross section. Goyal and Saretto (2009) show that delta-hedged options with a large positive difference between realized and implied volatility have low average returns. We examine a much larger set of both stock and option market predictors of option-implied volatilities than they use and use option volatilities themselves, rather than option straddle returns. Roll, Schwartz and Subrahmanyam (2009) examine the contemporaneous, but not predictive, relation between options trading activity and stock returns. Dennis and Mayhew (2002) document cross-sectional predictability of risk-neutral skewness, but do not examine the cross section of implied volatilities. We find many of the "usual suspects" in the commonly used stock characteristics that predict stock returns also predict the cross section of option-implied volatilities, like book-to-market ratios, momentum, and illiquidity measures. We focus on the strong predictive power of the lagged stock return in the cross section, which to our knowledge has been examined only in the context of options on the aggregate market by Amin, Coval and Seyhun (2004).

3. Data

3.1. Implied Volatilities

The daily data on option implied volatilities are from OptionMetrics. The OptionMetrics Volatility Surface computes the interpolated implied volatility surface separately for puts and calls using a kernel smoothing algorithm using options with various strikes and maturities. The underlying implied volatilities of individual options are computed using binomial trees that account for the early exercise of individual stock options and the dividends expected to be paid over the lives of the options. The volatility surface data contain implied volatilities for a list of standardized options for constant maturities and deltas. A standardized option is only included if there exists enough underlying option price data on that day to accurately compute an interpolated value. The interpolations are done each day so that no forward-looking information is used in computing the volatility surface. One advantage of using the Volatility Surface is that it avoids having to make potentially arbitrary decisions on which strikes or maturities to include in computing an implied call or put volatility for each stock. In our empirical analyses, we use call and put options' implied volatilities with a delta of 0.5 and an expiration of 30 days. For robustness we also examine other expirations, especially of 91 days, which are available in the internet appendix. Our sample is from January 1996 to September 2008. In the internet appendix, we also show that our results are similar using implied volatilities of actual options rather than the Volatility Surface.

Table 1 contains descriptive statistics of our sample. Panel A reports the average number of stocks per month for each year from 1996 to 2008. There are 1292 stocks per month in 1996 rising to 2175 stocks per month in 2008. We report the average and standard deviation of the end-of-month annualized call and put implied volatilities of at-the-money, 30-day maturities, which we denote as CVOL and PVOL, respectively. Both call and put volatilities are highest during 2000 and 2001 which coincides with the large decline in stock prices, particularly of technology stocks, during this time. During the recent finance crisis in 2008, we observe a significant increase in average implied volatilities from around 40% to 54% for both CVOL and PVOL.[3]

3.2. Predictive Variables

We obtain underlying stock return data from CRSP and accounting and balance sheet data from COMPUSTAT. We construct the following factor loadings and firm characteristics associated with underlying stock markets that are widely known to forecast the cross section of stock returns: [4]

Beta: To obtain the monthly beta of an individual stock, we estimate market model regressions at the daily frequency:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i (R_{m,d} - r_{f,d}) + \varepsilon_{i,d} \,, \qquad (1)$$

[3] There are many reasons why put-call parity does not hold, as documented by Ofek, Richardson and Whitelaw (2004) and Cremers and Weinbaum (2010), among others. In particular, the exchange-traded options are American and so put-call parity only holds as an inequality. The implied volatilities we use are interpolated from the Volatility Surface and do not represent actual transactions prices, which in options markets have large bid-ask spreads and non-synchronous trades. These microstructure issues do not affect the use of our option volatilities as predictive instruments observable at the beginning of each period.

[4] Easley, Hvidkjaer, and O'Hara (2002) introduce a measure of the probability of information-based trading, PIN, and show empirically that stocks with higher probability of information-based trading have higher returns. Using PIN as a control variable does not influence the significantly positive (negative) link between the call (put) volatility innovations and expected returns. We also examine the effect of systematic coskewness following Harvey and Siddique (2000). Including coskewness does not affect our results. See the internet appendix.

where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}$ is the market return on day d, and $r_{f,d}$ is the risk-free rate on day d. We take $R_{m,d}$ to be the CRSP daily value-weighted index and $r_{f,d}$ to be the Ibbotson risk-free rate. We estimate equation (1) for each stock using daily returns over the past month. The estimated slope coefficient $\hat{\beta}_{i,t}$ is the market beta of stock i in month t.

Size: Following the existing literature, firm size is measured by the natural logarithm of the market value of equity (stock price multiplied by the number of shares outstanding in millions of dollars) at the end of the month for each stock.

Book-to-Market Ratio (BM): Following Fama and French (1992), we compute a firm's book-to-market ratio in month t using the market value of its equity at the end of December of the previous year and the book value of common equity plus balance-sheet deferred taxes for the firm's latest fiscal year ending in prior calendar year. To avoid issues with extreme observations we follow Fama and French (1992) and Winsorize the book-to-market ratios at the 0.5% and 99.5% levels.

Momentum (MOM): Following Jegadeesh and Titman (1993), the momentum variable for each stock in month t is defined as the cumulative return on the stock over the previous 11 months starting 2 months ago to avoid the short-term reversal effect, i.e., momentum is the cumulative return from month t–12 to month t–2.

Illiquidity (ILLIQ): We use the Amihud (2002) definition of illiquidity and for each stock in month t define illiquidity to be the ratio of the absolute monthly stock return to its dollar trading volume: $ILLIQ_{i,t} = |R_{i,t}| / VOLD_{i,t}$, where $R_{i,t}$ is the return on stock i in month t, and $VOLD_{i,t}$ is the monthly trading volume of stock i in dollars.

Short-term reversal (REV): Following Jegadeesh (1990), Lehmann (1990), and others, we define short-term reversal for each stock in month t as the return on the stock over the previous month from t–1 to t.

Realized volatility (RVOL): Realized volatility of stock i in month t is defined as the standard deviation of daily returns over the past month t, $RVOL_{i,t} = \sqrt{\mathrm{var}(R_{i,d})}$. We denote the monthly first differences in RVOL as ΔRVOL.

The final set of predictive variables is from option markets:

Call/Put (C/P) volume: The relation between option volume and underlying stock returns has been studied in the literature, with mixed findings, by Stefan and Whaley (1990), Amin and Lee (1997), Easley, O'Hara, and Srinivas (1998), Chan, Chung, and Fong (2002), Cao, Chen, and Griffin (2005), and Pan and Poteshman (2006), and others. Following Pan and Poteshman (2006), our first measure of option volume is the ratio of call/put option trading volume over the previous month.

Call/Put open interest (C/P OI): A second measure of option volume is the ratio of open interests of call options to put options.

Realized-Implied volatility spread (RVOL-IVOL): Following Bali and Hovakimian (2009) and Goyal and Saretto (2009), we control for the difference between the monthly realized volatility (RVOL) and the average of the at-the-money call and put implied volatilities, denoted by IVOL, (using the Volatility Surface standardized options with a delta of 0.50 and maturity of 30 days). Bali and Hovakimian (2009) show that stocks with high RVOL-IVOL spreads predict low future stock returns. Goyal and Saretto (2009) find similar negative effect of the RVOL-IVOL spread for future option returns.

Risk-neutral skewness (QSKEW): Following Conrad, Dittmar and Ghysels (2009) and Xing, Zhang and Zhao (2010), we control for the risk-neutral skewness defined as the difference between the out-of-the-money put implied volatility (with delta of 0.20) and the average of the at-the-money call and put implied volatilities (with deltas of 0.50), both using maturities of 30 days. Xing, Zhang and Zhao (2010) show that stocks with high QSKEW tend to have low returns over the following month. On the other hand, Conrad, Dittmar and Ghysels (2009) find the opposite relation with a more general measure of option skewness derived from using the entire cross section of options based on Bakshi, Kapadia and Madan (2003).

3.3. Measures of Volatility Innovations

First Differences of Implied Volatility Levels

The first, and simplest, definition of volatility innovations is the change in call and put implied volatilities, which we denote as ΔCVOL and ΔPVOL, respectively:[5]

$$\begin{aligned}\Delta CVOL_{i,t} &= CVOL_{i,t} - CVOL_{i,t-1},\\ \Delta PVOL_{i,t} &= PVOL_{i,t} - PVOL_{i,t-1}.\end{aligned} \tag{2}$$

While the first difference of implied volatilities is a very attractive measure because it is simple, it ignores the fact that implied volatilities are predictable in both the time series and cross section. Our two other measures account for these dimensions of predictability.

Time-Series Innovations

Implied volatilities are well known to be persistent. To take account of the autocorrelation, we assume an AR(1) model for implied volatilities and estimate the following regression using the past two years of monthly data:

$$\begin{aligned}CVOL_{i,t} &= a_{ci} + b_{ci} \cdot CVOL_{i,t-1} + \varepsilon^{c}_{i,t},\\ PVOL_{i,t} &= a_{pi} + b_{pi} \cdot PVOL_{i,t-1} + \varepsilon^{p}_{i,t}.\end{aligned} \tag{3}$$

We define the current shock in call and put implied volatilities for stock i in month t as the monthly innovations in call and put implied volatilities. That is, we assign the time t value of $\varepsilon^{c}_{i,t}$ and $\varepsilon^{p}_{i,t}$ as the option innovations and denote them as $\mathrm{CVOL}^{\mathrm{shock}}_{\mathrm{ts}}$ and $\mathrm{PVOL}^{\mathrm{shock}}_{\mathrm{ts}}$, respectively, with the "ts" subscript denoting that they are innovations derived from time-series estimators. Note that the ΔCVOL and ΔPVOL first difference measures implicitly assume that $b_{ci} = b_{pi} = 1$.

Cross-Sectional Innovations

We can alternatively estimate monthly innovations in volatilities by exploiting the cross-sectional predictability of implied volatilities. We denote the cross-sectional innovations as $\mathrm{CVOL}^{\mathrm{shock}}_{\mathrm{cs}}$ and

[5] As an additional robustness check, we also consider proportional changes in CVOL and PVOL and find very similar results. The results from the percent changes in call and put implied volatilities (%ΔCVOL, %ΔPVOL) are available in the internet appendix.

$\mathrm{PVOL}_{\mathrm{cs}}^{\mathrm{shock}}$, with the "cs" subscript denoting they are cross-sectional estimators of implied volatility innovations, and estimate them using firm-level cross-sectional regressions for each month *t*:

$$
\begin{aligned}
CVOL_{i,t} &= a_{ct} + b_{ct} \cdot CVOL_{i,t-1} + \varepsilon_{i,t}^{c} \\
PVOL_{i,t} &= a_{pt} + b_{pt} \cdot PVOL_{i,t-1} + \varepsilon_{i,t}^{p},
\end{aligned}
\tag{4}
$$

where the cross section of call and put implied volatilities are regressed on their one-month lagged values for each month *t*. The residuals of these cross-sectional regressions at time *t*, $\varepsilon_{i,t}^{c}$ and $\varepsilon_{i,t}^{p}$, are used as measures of volatility innovations, denoted by $\mathrm{CVOL}_{\mathrm{cs}}^{\mathrm{shock}}$ and $\mathrm{PVOL}_{\mathrm{cs}}^{\mathrm{shock}}$, respectively.

Correlations of Volatility Innovations

Panel B of Table 1 presents the average firm-level cross correlations of the level and innovations in implied and realized volatilities. The average correlation between the levels of call and put implied volatilities (CVOL and PVOL) is 92%. This high correlation reflects a general volatility effect, indicating that when current stock volatility increases, all option contracts across all strikes and maturities reflect this general increase of volatility. Note that if put-call parity held exactly, then the correlation of CVOL and PVOL would be one. Both CVOL and PVOL have a correlation of 67% with past realized volatility which reflects the persistence of volatility.

The first differences in implied volatilities, ΔCVOL and ΔPVOL, are less correlated, at 57%, than the levels CVOL and PVOL, which have a correlation of 92%. This lower correlation implies that the cross section of put volatility innovations may contain different information from the cross section of call volatility innovations, which we confirm below, but nevertheless indicates that there is a strong common component in both call and put volatility innovations. The changes in implied volatilities are not correlated with either RVOL or ΔRVOL, with correlations of ΔCVOL with RVOL and ΔRVOL being 0.04 and 0.10, respectively. The correlations of ΔPVOL with RVOL and ΔRVOL are also low at 0.05 and 0.11, respectively. This shows that the forward-looking CVOL and PVOL estimates are reacting to more than just past volatility captured by RVOL and that innovations in implied volatilities represent new information not captured by backward-looking volatility measures.

The time-series and cross-sectional innovations of CVOL and PVOL are similar to the first-difference estimates. This is seen in the high correlations of ΔCVOL with $\mathrm{CVOL}_{\mathrm{ts}}^{\mathrm{shock}}$, at 0.83, and of ΔCVOL with $\mathrm{CVOL}_{\mathrm{cs}}^{\mathrm{shock}}$, at 0.95. Similarly ΔPVOL has correlations of 0.81 and 0.95 with $\mathrm{PVOL}_{\mathrm{ts}}^{\mathrm{shock}}$ and $\mathrm{PVOL}_{\mathrm{cs}}^{\mathrm{shock}}$, respectively. Thus, all three measures of implied volatility innovations have high degrees of comovement and it would not be surprising for all the innovation measures to have roughly the same degree of predictive ability. We verify this is the case below.

4. Predicting the Cross Section of Stock Returns with Implied Volatilities

We investigate the cross-sectional relation between implied volatility shocks and expected stock returns at the firm level using cross-sectional regressions. These regressions take the form:

$$R_{i,t+1} = \lambda_{0t} + \lambda_{1t} \cdot X_{i,t} + \varepsilon_{i,t+1}, \tag{5}$$

where $R_{i,t+1}$ is the realized return on stock i in month t+1 and $X_{i,t}$ is a collection of stock-specific variables observable at time t for stock i, which includes information from the cross section of stocks and the cross section of options. Following Fama and MacBeth (1973), we estimate the regression in equation (5) across stocks i at time t and then report the cross-sectional coefficients λ_{1t} averaged across the sample. The cross-sectional regressions are run at the monthly frequency over 152 months from February 1996 to September 2008. To compute standard errors we take into account potential autocorrelation and heteroscedasticity in the cross-sectional coefficients and compute Newey-West (1987) t-statistics on the time series of slope coefficients. The Newey-West standard errors are computed with six lags.

4.1. Predicting Returns with First-Difference Innovations of Implied Volatilities

We start in Table 2 by investigating the predictive power of volatility levels for the full sample period. Regressions (1) and (2) in Panel A use the level of option implied volatilities CVOL and PVOL, respectively, while regression (3) sets RVOL as the regressor. We report Newey-West (1987) adjusted t-statistics in parentheses. In regressions (1)-(3) all the coefficients are negative and statistically insignificant. The negative coefficient on the realized or option volatilities is consistent with the well-known leverage effect operating at the individual stock level (see, among many others, Bekaert and Wu, 2000; Figlewski and Wang, 2000) where high volatilities forecast low stock returns. From these results we cannot reject the hypothesis that there is no link between the *level* of implied and realized volatilities and the cross section of expected returns.

In regressions (4)-(8) of Panel A, Table 2, we test whether first-difference innovations of implied and realized volatilities predict the cross section of stock returns. In regression (4), the slope on ΔCVOL is 1.87 with a t-statistic of 2.90. The coefficient on ΔPVOL is –0.95 with a t-statistic of –2.09 in regression (5). In contrast, there is no predictive power of changes in RVOL in regression (6), which has a coefficient close to zero with a t-statistic of 0.30. Thus, unexpected news in implied volatilities, but not past volatilities, cross-sectionally predict stock returns. Unexpectedly high call volatilities forecast increases in future stock returns, while unexpectedly high put volatilities predict declines in future stock returns.

The positive coefficient on ΔCVOL and the negative coefficient on ΔPVOL are consistent with each other. An informed "bullish" trader who has good information that a stock is likely to go up next period, but the market does not completely react to the trades of that informed investor this period, can buy a call, which increases call option volatilities this period, or sell a put, which decreases put option volatilities this period. Thus, increases in ΔCVOL and decreases in ΔPVOL both forecast increases in next-month stock returns. A similar story holds for a "bearish" informed investor betting a stock will decrease in value. This investor can buy a put or sell a call, so increases in put volatilities or decreases in call volatilities then predict stock price declines. While the signs of the coefficients on ΔCVOL and ΔPVOL are consistent, the effect of ΔCVOL is economically larger, at 1.87, which is approximately twice the size in absolute value compared to the coefficient on ΔPVOL, which is –0.95 (even though both are statistically significant at the 95% level). This indicates that used alone, the innovations from call option volatilities contain more predictive power, but this does not control for any other stock-specific risk factors or characteristics (see below).

We expect that we should obtain both economic and statistical benefit from using ΔCVOL and ΔPVOL jointly. Economically because we expect the largest effects to be on those stocks with the largest positive changes in CVOL *and* the largest negative changes in PVOL as the payoffs from calls and puts are in opposite directions. Statistically because the correlations between ΔCVOL and ΔPVOL are not that high at 0.57 (see Table 1), and since there is no collinearity we can simultaneously control for each effect. We examine the bivariate specification in regression (7). Panel A, Table 2 shows the coefficients on ΔCVOL and ΔPVOL are 3.59 and –2.86, respectively, and both are highly significant with t-statistics of 5.02 and –5.32, respectively. The statistical significance of these coefficients is much stronger when including changes in both call and put volatilities jointly in regression (7) compared to the univariate regressions (4) and (5). Regression (8) includes ΔRVOL as an additional regressor and we find the coefficients on ΔCVOL and ΔPVOL are almost unchanged and the coefficient on ΔRVOL is very close to zero.

Cremers and Weinbaum (2010) investigate in detail how the call-put volatility spread, which is the difference between CVOL and PVOL, predicts stock returns. They also investigate changes in volatility spreads, ΔCVOL – ΔPVOL, but only in passing. They do not focus on univariate predictability of ΔCVOL or ΔPVOL or unconstrained joint predictability of these variables. Cremers and Weinbaum point out that the strength of predictability from call-put volatility spreads declines during their sample period becoming insignificant over the second half of their sample, 2001-2005. We now show that the predictability from using ΔCVOL and ΔPVOL is robust to different sample periods including more recent samples.

Panel B of Table 2 reports subsample analysis for the bivariate ΔCVOL and ΔPVOL cross-sectional regressions using options with 30 days to maturity. We first decompose the original sample period of January 1996–September 2008 into two subsamples: January 1996 to December 2001 and January 2002 to September 2008. Panel B of Table 2 reports the full sample coefficients in the first column, which are identical to regression (7) in Panel A for comparison. As shown in the second two columns of Panel B, the average slopes on ΔCVOL and ΔPVOL are positive and negative, respectively, and both are highly significant in the two sample periods. The coefficient on ΔCVOL is slightly lower, at 2.96, over the second subsample compared to a value of 3.60 over the whole sample, but is still statistically significant at the 99% level with a Newey-West t-statistic of 2.92. In comparison the coefficients on ΔPVOL are relatively unchanged across the whole sample at –2.86 and across each subsample, with coefficients of –2.60 and –3.09, respectively.

In the last column of Panel B, we investigate the predictive power of ΔCVOL and ΔPVOL during the financial crisis in 2008. During this period volatilities on all stocks increased tremendously. Panel B reports that the coefficients on both ΔCVOL and ΔPVOL remain positive and negative, respectively, with coefficients of 2.50 and –2.28, respectively. These are similar to the full sample estimates of 3.60 for ΔCVOL and –2.86 for ΔPVOL. Despite the very short sample of only nine months, the coefficient on ΔPVOL is even highly statistically significant with a Newey-West t-statistic of –4.28. Clearly the recent financial crisis has not dented the predictive ability of these variables.

Overall, these results indicate strong significance of the call and put implied volatility shocks as joint determinants of the cross-section of future returns. Increases in call volatilities forecast increases in stock expected returns and increases in put volatilities act in the opposite direction forecasting decreases in future stock returns.[6]

4.2. Implied Volatility Innovations and Other Cross-Sectional Predictors

Table 3 presents firm-level cross-sectional regressions with volatility innovations first introduced individually and then simultaneously, together with controls for firm characteristics and risk factors. We

[6] When using options with 91 days to maturity, we find somewhat stronger results. The predictability over the next month is not concentrated in the first few trading days of that month and is evenly spread throughout that month. We report these results in the internet appendix.

also include ΔCVOL and ΔPVOL simultaneously in multivariate regressions with control variables to determine their joint effects on stock returns. In the presence of risk loadings and firm characteristics, the coefficient on ΔCVOL falls from 1.87 in Table 3 to 1.49 in regression (1) in Table 4, but is still significant with a t-statistic of 2.41. In regression (2), the coefficient on ΔPVOL is –2.07 with a t-statistic –3.94. This is actually much larger in magnitude than the corresponding coefficient of –0.95 on ΔPVOL in Table 2 (Panel A), which does not control for other predictors. Regression (3) includes both ΔCVOL and ΔPVOL with coefficients of 3.65 and –3.84, with t-statistics of 4.83 and –5.29, respectively. For comparison, without control variables the coefficients are 3.60 and –2.86, respectively, so controlling for other risk loadings and characteristics has little bearing on the magnitude of the ΔCVOL predictive coefficient and significantly increases the magnitude of the ΔPVOL coefficient. In regression (4), we drop RVOL and replace it by the RVOL-IVOL spread. We do not include RVOL and RVOL-IVOL in the same regression because they are very highly correlated. The ΔCVOL and ΔPVOL coefficients are similar across regressions (3) and (4). In summary, Table 3 shows the positive coefficient on ΔCVOL and the negative coefficient on ΔPVOL are robust to the standard cross-sectional predictors and have very strong statistical power in the presence of the standard risk variables.

To provide an economic significance of the average slope coefficients in Table 3 on ΔCVOL and ΔPVOL, we construct the empirical cross-sectional distribution of implied volatility innovations over the full sample (summarized in Panel A, Table 1). The difference in ΔCVOL values between average stocks in the first and fifth quintiles is 19.29% for call implied volatility innovations, whereas the difference in ΔPVOL values between average stocks in the first and fifth quintiles is 18.10% for put implied volatility innovations. If a firm were to move from the first quintile to the fifth quintile of implied volatilities while its other characteristics were held constant, what would be the change in that firm's expected return? The ΔCVOL coefficient of 3.65 in Table 3 represents an economic effect of an increase of $3.65 \times 19.29\% = 0.70\%$ per month in the average firm's expected return of a firm moving from the first to the fifth quintile of implied volatilities, and the ΔPVOL coefficient of –3.84 represents a similar decrease of $-3.84 \times 18.10\% = 0.69\%$ per month. These are large economic effects.

Other Cross-Sectional Predictors

In Table 3 the signs of the estimated Fama-MacBeth coefficients on the stock characteristics are consistent with earlier studies, but the relations are generally not statistically significant. The log market capitalization (SIZE) and log book-to-market ratio (BM) coefficients indicate a small-large and a value-growth effect with negative and positive coefficients, respectively, but both are insignificantly different from zero. The momentum (MOM) and short-term reversal (REV) effects are also statistically weak.

This is because we use optionable stocks that are generally large and liquid where the book-to-market effect is weaker (see Loughran, 1997). Optionable stocks are significantly different from the usual CRSP universe which contains many more small, illiquid, and low-priced stocks with strong reversal and momentum effects (cf. Hong, Lim and Stein, 2000).

The most interesting predictors for our purposes, however, are the ones that are related to volatility and the option market. In regressions (1)-(3), the coefficient on historical volatility, RVOL, is negative and highly statistically significant. This is very similar to the cross-sectional volatility effect of Ang et al. (2006, 2009) where stocks with high past volatility have low returns, except Ang et al. work mainly with idiosyncratic volatility defined relative to the Fama and French (1993) model instead of total volatility. The results are unchanged if idiosyncratic volatility is used. Panel B of Table 1 reports that RVOL has very low correlations of 0.04 and 0.05 with ΔCVOL and ΔPVOL, respectively. This indicates that the effect of past volatility is very different from our cross-sectional predictability of ΔCVOL and ΔPVOL.

Pan and Poteshman (2006) find that stocks with high C/P Volume outperform stocks with low call-put volume ratios by more than 40 basis points on the next day and more than 1% over the next week. Our results in Table 3 show that there is a positive relation between C/P Volume and the cross-section of expected returns, but C/P Volume is not significant in regression (1). This is consistent with Pan and Poteshman who show that publicly available option volume information contains little predictive power whereas their proprietary measure of option volume from private information does predict future stock returns. As an alternative to option trading volume, we also examine C/P OI. This variable is highly insignificant with a coefficient close to zero.

There are mixed effects from other implied volatility measures. In regression (4) RVOL-IVOL carries an insignificant coefficient, but the negative coefficient is consistent with Bali and Hovakimian (2009).[7] In regressions (1)-(4), the coefficients on risk-neutral skewness, QSKEW, are negative and highly significant. This confirms the negative predictive relation between option skew and future stock returns, as in Xing, Zhang and Zhao (2010). The highly statistically significant loadings on ΔCVOL and ΔPVOL in the presence of the negative QSKEW coefficient imply that the information in option volatility innovations is different from the previously documented predictive ability of the option skew for the cross section of stock returns.

[7] The RVOL-IVOL variable, however, is significant at the 95% level using 91 days to maturity. QSKEW loses its statistical significance at this maturity. In contrast, ΔCVOL and ΔPVOL are significant for both 30 and 91 days to maturity. See the internet appendix.

The clear conclusion in Table 3 is that cross-sectional regressions with and without risk controls provide strong evidence for a significantly positive (negative) relation between the changes in call (put) options' implied volatilities and future stock returns.

4.3. Time-Series and Cross-Sectional Innovations of Implied Volatilities

In Table 4 we extend our analysis to the time-series and cross-sectional measures of option volatility innovations. The results in Table 4 echo the main conclusions in Table 3. This is perhaps not surprising since Table 1 shows the correlations between the time-series innovations, $CVOL_{ts}^{shock}$ and $PVOL_{ts}^{shock}$, and the cross-sectional innovations, $CVOL_{cs}^{shock}$ and $PVOL_{cs}^{shock}$, with the simple first-difference counterparts $\Delta CVOL$ and $\Delta PVOL$ are very high.

The left panel of Table 4 presents results from the cross-sectional measures of volatility innovations, $CVOL_{cs}^{shock}$ and $PVOL_{cs}^{shock}$. Again the coefficients on the CVOL innovations are always positive and the PVOL innovations are always negative. Let us focus on regression (3). The coefficient on $CVOL_{cs}^{shock}$ is 3.78 with a t-statistic of 4.72 and the coefficient on $PVOL_{cs}^{shock}$ is –4.14 with a t-statistic of –5.69.[8] These are very similar to the coefficients on $\Delta CVOL$ and $\Delta PVOL$, which are 3.65 and –3.85, respectively, in Table 3.

In the right panel of Table 4, we can draw similar conclusions using the time-series measures of volatility innovations, $CVOL_{ts}^{shock}$ and $PVOL_{ts}^{shock}$. In the joint regression (3), the coefficients on $CVOL_{ts}^{shock}$ and $PVOL_{ts}^{shock}$ are 5.07 and –5.27, both with absolute t-statistics above 4.0. These are both larger in magnitude than the simple $\Delta CVOL$ and $\Delta PVOL$ innovations and the cross-sectional $CVOL_{ts}^{shock}$ and $PVOL_{ts}^{shock}$ measures.

4.4. Systematic vs. Idiosyncratic Volatility Innovations

Implied call and put volatilities contain both systematic and idiosyncratic components. We now investigate if the predictive information in implied volatility innovations reflects news arrivals in systematic risk, idiosyncratic components, or both. This exercise sheds light on whether the forecasting power of call and put volatility innovations is coming from news in risk premium components, at least measured by exposure to the market factor, or by firm-specific sources.

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[8] The coefficients on the cross-sectional shocks are slightly larger in absolute value when we augment the regression in equation (4) with one-month lagged realized volatilities for each firm *i* at time *t*.

We decompose the total implied variance into a systematic component and an idiosyncratic component using a conditional CAPM relation:

$$\sigma_{i,t}^2 = \beta_{i,t}^2 \sigma_{m,t}^2 + \sigma_{\varepsilon,i,t}^2 , \tag{6}$$

where $\sigma_{i,t}^2$ is the risk-neutral variance of stock *i*, $\sigma_{m,t}^2$ is the risk-neutral variance of the market *m*, $\beta_{i,t}$ is the market beta of stock *i,* and $\sigma_{\varepsilon,i,t}^2$ is the idiosyncratic risk-neutral variance of stock *i,* all at time *t*. We estimate betas by using stock returns and also use beta estimates implied by option prices.

Real Measure Betas

We refer to betas estimated from stock returns as physical or real measure betas. These are estimated using the past one year of daily returns on individual stocks and the market portfolio. We define the systematic and idiosyncratic call implied volatilities as:

$$\begin{aligned} CVOL_{i,t}^{sys} &= \beta_{i,t}\sigma_{m,t} \\ CVOL_{i,t}^{idio} &= \sigma_{\varepsilon,i,t} = \sigma_{i,t} - \beta_{i,t}\sigma_{m,t} , \end{aligned} \tag{7}$$

where the betas are from the physical measure. We use the corresponding expressions $PVOL_{i,t}^{sys}$ and $PVOL_{i,t}^{idio}$ when put implied volatilities along with the corresponding betas are used to decompose the changes in put implied volatilities. The systematic vs. idiosyncratic decomposition is in terms of standard deviations and follows Ben-Horian and Levy (1980) and others, and it is consistent with our previous empirical work looking at changes in option volatilities, rather than variances. We consider the predictive ability of first-difference innovations $\Delta\text{CVOL}^{\text{sys}}$, $\Delta\text{PVOL}^{\text{sys}}$, $\Delta\text{CVOL}^{\text{idio}}$, and $\Delta\text{PVOL}^{\text{idio}}$ on the cross section of stock returns. As expected, the cross-sectional correlation of the innovations in the systematic component of volatilities, $\Delta\text{CVOL}^{\text{sys}}$ and $\Delta\text{PVOL}^{\text{sys}}$, is very high at above 0.99, whereas the correlation between the idiosyncratic terms, $\Delta\text{CVOL}^{\text{idio}}$ and $\Delta\text{PVOL}^{\text{idio}}$, is much lower at 0.84.

In Table 5, we break up the innovations of ΔCVOL and ΔPVOL into systematic and idiosyncratic components while controlling for the usual risk characteristics. Due to the extremely high correlation between the systematic $\Delta\text{CVOL}^{\text{sys}}$ and $\Delta\text{PVOL}^{\text{sys}}$ terms, we include only one term in each regression. In the left panel of Table 5, we decompose the systematic and idiosyncratic components using real measure betas. The panel shows that the coefficients on $\Delta\text{CVOL}^{\text{idio}}$ are positive, around 1.8, and statistically significant with t-statistics above 3.0. The coefficients on $\Delta\text{PVOL}^{\text{idio}}$ are approximately –2.4 with t-statistics around –4.0. The positive coefficients on $\Delta\text{CVOL}^{\text{idio}}$ and the negative coefficients on $\Delta\text{PVOL}^{\text{idio}}$ are reminiscent of the positive and negative coefficients on ΔCVOL and ΔPVOL, respectively, in Tables 2 and 3. The coefficients on the systematic components are negative, but statistically insignificant. Clearly it is changes in the idiosyncratic volatility components that are driving the predictability.

Risk-Neutral Betas

We next examine betas estimated using option prices, which we term risk-neutral betas. Christoffersen, Jacobs and Vainberg (2008) argue that betas computed from option prices contain different information than betas estimated from stock returns.

Following Duan and Wei (2009), we infer a risk-neutral beta using the risk-neutral skewness of the individual stock, $Skew_{i,t}$, and the risk-neutral skewness of the market, $Skew_{m,t}$, using the following relation:

$$Skew_{i,t} = \beta_{i,t}^{3/2} Skew_{m,t}, \tag{8}$$

where the risk-neutral measures of skewness are estimated following Bakshi, Kapadia, and Madan (2003). We provide further details in the Appendix. The volatility innovations for the systematic and idiosyncratic components are computed using equation (7) except the risk-neutral betas are used instead of the physical betas. Similar to the physical betas, the correlation between the systematic components $\Delta CVOL^{sys}$ and $\Delta PVOL^{sys}$ computed using risk-neutral betas is very high at above 0.99. The correlation between $\Delta CVOL^{idio}$ and $\Delta PVOL^{idio}$ using risk-neutral betas is 0.64.

The right-hand panel in Table 5 reports the result of the systematic vs. idiosyncratic decomposition using risk-neutral betas. We again observe the coefficients on the systematic components on $\Delta CVOL^{sys}$ and $\Delta PVOL^{sys}$ are statistically insignificant, but they have changed sign compared to their counterparts computed using physical betas. The coefficient on $\Delta CVOL^{idio}$ is around 1.5 with t-statistics of approximately 3.1 and the coefficient on $\Delta PVOL^{sys}$ is approximately –2.3 with t-statistics of –3.9. These coefficients are very similar to the ones computed using physical betas.

In summary, the predictive ability of innovations in call and put volatilities for the cross section of stock returns stems from idiosyncratic, not systematic, components in volatilities and this result is robust to alternative measures of market beta. Thus if the predictability from ΔCVOL and ΔPVOL is arising from informed investors placing trades in option markets, these investors tend to have better information about future company-specific news or events rather than the way these stocks are reacting to systematic factor risk.

5. Returns on Option Volatility Innovation Portfolios

We now examine the potential investable returns that can be generated by forming portfolios sorted on option implied volatility innovations.[9] We concentrate on the simplest measures of option volatility innovations, ΔCVOL and ΔPVOL.

5.1. Portfolios Ranked on ΔCVOL and ΔPVOL

Univariate Portfolios

In Panel A of Table 6 we form quintile portfolios ranked on ΔCVOL rebalanced every month. Portfolio 1 (Low ΔCVOL) contains stocks with the lowest changes in call implied volatilities in the previous month and Portfolio 5 (High ΔCVOL) includes stocks with the highest changes in call implied volatilities in the previous month. We equal weight stocks in each quintile portfolio and rebalance monthly. Panel A of Table 6 shows the average raw return of stocks in quintile 1 with the lowest ΔCVOL is 0.10% per month and this monotonically increases to 1.07% per month for stocks in quintile 5. The difference in average raw returns between quintiles 1 and 5 is 0.97% per month with a highly significant Newey-West t-statistic of 3.37. This translates to a monthly Sharpe ratio of 0.28 and an annualized Sharpe ratio of 0.98 for a strategy with monthly rebalancing going long High ΔCVOL stocks and shorting Low ΔCVOL stocks. The differences in returns between quintiles 1 and 5 are very similar if we risk adjust using the CAPM, at 0.94% per month, and the Fama-French (1993) model [FF3 hereafter] including market, size and book-to-market factors, at 0.90% per month. In the final column, we do a characteristic match similar to Daniel and Titman (1997) and Daniel et al. (1997). This reduces the quintile 1 and 5 difference to 0.71% per month, but this is still both economically large and statistically significant.

In Panel B, we form quintile portfolios ranked on ΔPVOL rebalanced every month. Portfolio 1 (Low ΔPVOL) contains stocks with the lowest changes in put implied volatilities in the previous month and Portfolio 5 (High ΔPVOL) includes stocks with the highest changes in put implied volatilities in the previous month. Unlike the monotonically increasing returns in the ΔCVOL portfolios, there is effectively no pattern across the first four ΔPVOL portfolios – but there is a pronounced, much lower average return of the fifth ΔPVOL quintile, which is 0.45% per month, on average, compared to 0.76% per month for the other quintile portfolios. It is this large drop that the univariate cross-sectional regression largely picks up and the OLS coefficient is statistically significant in that context (see Table 2).

[9] Our results are robust if we skip the last day of the month in computing the change in implied volatilities and form portfolios. These results are available in the internet appendix.

Consistent with the ΔPVOL effect becoming stronger in the cross-sectional regressions as we control for more variables, the spread between the first and fifth ΔPVOL portfolios increases in absolute value as we control for the CAPM, the Fama-French model, and is actually statistically significant when we add characteristic controls, at –0.28% per month with a t-statistic of –2.51. In all these cases, however, the most pronounced pattern is the large decrease in returns for stocks where there are large changes in put option implied volatilities.

Like the cross-sectional regressions, we should expect the predictability of ΔCVOL and ΔPVOL to be best exploited when jointly controlling for both effects – we should see stock returns increase most for those stocks where bullish investors drive upwards call option volatilities *and* simultaneously drive downwards put option volatilities. We can jointly control for ΔCVOL and ΔPVOL effects in portfolios by constructing bivariate portfolio sorts, which we turn to now.

Bivariate Portfolios

In Panels C and D of Table 6, we examine the predictive ability of the changes in call and put implied volatilities based on the dependent and independent sorts of individual stocks into portfolios ranked on ΔCVOL and ΔPVOL. We present *dependent* (conditional) sorts.[10]

In Panel C, we perform a sequential sort by creating quintile portfolios ranked by past ΔPVOL. Then, within each ΔPVOL quintile we form a second set of quintile portfolios ranked on ΔCVOL. This creates a set of portfolios with similar past ΔPVOL characteristics with spreads in ΔCVOL and thus examines expected return differences due to ΔCVOL rankings controlling for the effect of ΔPVOL. We hold these portfolios for one month and then rebalance at the end of the month. Table 6, Panel C reports the monthly percentage raw returns of these portfolios. As we move across the columns in Panel C, the returns generally increase from low to high ΔCVOL. The largest average portfolio returns are found near the top right-hand corner of Panel C, consistent with informed investors trading in option markets today to generate large positive ΔCVOL and large negative ΔPVOL changes which predict stock price movements next period. Conversely, the most negative portfolio returns lie in the bottom left-hand corner where the largest ΔPVOL changes and the most negative ΔCVOL movements predict future decreases in stock prices.

In a given ΔPVOL quintile portfolio, we can take the differences between the last and first ΔCVOL return quintiles. We then average these return differentials across the ΔPVOL portfolios. This

[10] It is possible to construct bivariate portfolios ranking on ΔCVOL and ΔPVOL based on independent sorts, which are reported in the internet appendix. Briefly, the return differences produced using independent sorts are larger than the ones reported in Table 6. Controlling for ΔPVOL, the average difference in returns (FF3 Alphas) between extreme ΔCVOL quintile portfolios is 1.49% (1.45%) per month. Controlling for ΔCVOL, the average difference in returns (FF3 Alphas) between extreme ΔPVOL quintile portfolios is –0.89% (–0.93%) per month.

procedure creates a set of ΔCVOL portfolios with nearly identical levels of ΔPVOL. Thus, we have created portfolios ranking on ΔCVOL but controlling for ΔPVOL. If the return differential is entirely explained by ΔPVOL, no significant return differences will be observed across ΔCVOL quintiles. These results are reported in the column called "ΔCVOL5 – ΔCVOL1". All of these differences are above 1% per month and are highly statistically significant. Panel C of Table 6 shows that the average raw return difference between the high ΔCVOL and low ΔCVOL quintiles is 1.13% per month with a t-statistic of 5.39. The average FF3 Alpha difference between the first and fifth ΔCVOL quintiles averaged across the ΔPVOL portfolios is 1.12% per month with a t-statistic of 4.95.[11]

In Panel D, we repeat the same exercise as Panel C but perform sequential sorts first on ΔCVOL and then on ΔPVOL. This produces sets of portfolios with different ΔPVOL rankings after controlling for the information contained in ΔCVOL. This set of sequential sorts produces lower returns as ΔPVOL increases consistent with the negative coefficients on ΔPVOL in the cross-sectional regressions. The negative relation between increasing ΔPVOL and lower average returns is repeated in every ΔCVOL quintile and is impressively monotonically decreasing in all cases. The last two rows of Panel D average the differences between the first and fifth ΔPVOL quintiles across the ΔCVOL quintiles. This summarizes the returns to ΔPVOL after controlling for ΔCVOL. The average return difference is –0.63% per month with a t-statistic of –4.81. The average difference in FF3 alphas is very similar at –0.68% per month with a t-statistic of –5.51. Again there is a strong negative relation between ΔPVOL and stock returns in the cross section.

In Panels C and D of Table 6, we also report the change in volume and open interest of calls and puts. Call volume and open interest tends to increase with the change in call implied volatilities. This is also true for put volume and open interest. This is consistent with the interpretation that the increase in implied volatilities may be due to investor demand with fresh information, along the lines of Bollen and Whaley (2004) and Garleanu, Pedersen and Poteshman (2009). This increased demand, and the contemporaneous effect on option volatilities, may be due to the trading of options by certain investors with better information, which is borne out next period in the stock market.

Lack of Response of Option Markets

The firm-level cross-sectional regressions in Tables 2 and 3 and the portfolio level analysis in Table 6 convincingly show the stock market reacts to option market information. As Table 6 shows, the large

[11] If we augment the Fama-French (1993) regression with additional factors for momentum and short-term reversals, the alphas are almost unchanged. These numbers are available in the internet appendix.

changes in option prices occur contemporaneously with option volume. Is all this information impounded in option prices today?[12]

We investigate this issue by looking at the pattern of implied volatilities in the pre- and post-formation months. Taking the dependent 5×5 sorts constructed in Table 6, we compute the call and put implied volatilities from month t–6 to month t+6. In Figure 1, Panel A, we plot the level of call implied volatilities for the Low ΔCVOL and High ΔCVOL quintiles from the dependent sorts of ΔCVOL and ΔPVOL portfolios formed at time t from month t–6 to month t+6. For the Low ΔCVOL quintile, call implied volatilities decrease from 61% to 49% from month t–1 to month t, but then they increase to 52% in month t+1 and remain at about the same level over the next six months. Similarly, for the High ΔCVOL quintile, call implied volatilities first increase from 48% to 60% from month t–1 to month t, but then they decrease to 55% in month t+1 and remain around there over the next six months. Panel B of Figure 1 repeats the same exercise for the Low ΔPVOL and High ΔPVOL quintiles and also shows that there is no movement in put implied volatilities in the post-formation months; all of the adjustment to the option information takes place only in equity markets. This is consistent with the interpretation that informed traders move option prices today and there is no other adjustment, on average, in option markets while equity returns adjust over the next month.

5.2. Size Effect

In Table 7, we examine the predictability of implied volatility innovations in different size buckets. We sort optionable stocks into two groups based on their market capitalization (Small vs. Big). Within each group of stocks (Small and Big), we perform the same dependent rankings as Table 6 where we form ΔCVOL portfolios controlling for ΔPVOL and ΔPVOL portfolios controlling for ΔCVOL.

Table 7 reports the average raw and alpha differences between the extreme quintile portfolios in the Small and Big stock groups.[13] The results show that the average raw and alpha differences between the first and fifth ΔCVOL portfolios are positive and significant in each group of stocks: the average return difference between the highest and lowest quintiles ranked on ΔCVOL across the ΔPVOL quintiles is 1.45% per month for small stocks and 0.61% for large stocks. Although both are highly statistically significant, there is a smaller, but still economically large, effect in the big stock group. We observe a similar phenomenon for the ΔPVOL effect. The average return difference between the highest and lowest quintiles ranked on ΔPVOL across the ΔCVOL quintiles is –0.87% per month for small stocks and this

[12] We thank a referee for suggesting this analysis.
[13] See the internet appendix for raw average returns for further details including the returns on each 5×5 portfolio.

reduces to –0.37% per month for large stocks. In both cases, the Newey-West t-statistics are still significant.

The reduction, but not elimination, of the anomalous returns in the bigger stock group indicates that there may be some liquidity frictions involved in implementing a tradable strategy based on ΔCVOL and ΔPVOL predictors. Table 7 shows that the effect is not eliminated in the larger, more liquid stocks. In the internet appendix, we present further results for other screens related to liquidity and transactions costs, such as excluding the smallest, lowest-priced, and least-liquid stocks in the formation of our portfolios. In all cases, there remain economically and statistically significant next-month returns from forming simple portfolios ranked on ΔCVOL and ΔPVOL.

5.3. Long-Term Predictability

So far we have examined only the next-month returns. In this section, we consider the longer-term predictive power of ΔCVOL and ΔPVOL over the next six months. We follow Jegadeesh and Titman (1993) and construct simultaneous portfolios with overlapping holding periods. In a given month t, the strategy holds a series of portfolios that are selected in the current month as well as in the previous $K-1$ months, where K is the holding period ($K = 1$ to 6 months). At the beginning of each month t, we perform dependent sorts on ΔCVOL controlling for ΔPVOL over the past month. Based on these rankings, five quintile portfolios are formed for ΔCVOL. In each month t, the strategy buys stocks in the High ΔCVOL quintile and sells stocks in the Low ΔCVOL quintile, holding this position for K months. In addition, the strategy closes out the position initiated in month $t-K$. Hence, under this trading strategy we revise the weights on $1/K$ of the stocks in the entire portfolio in any given month and carry over the rest from the previous month. Quintile portfolios of ΔPVOL are formed similarly. The profits of the above strategies are calculated for a series of portfolios that are rebalanced monthly to maintain equal weights.

We report the long-term predictability results in Table 8. The average raw and risk-adjusted return differences between High ΔCVOL and Low ΔCVOL portfolios are statistically significant for one- to six-month holding periods. There is a pronounced drop in the magnitude of the average holding return, which more than halves between months 1 and 2 from 1.13% per month to 0.49% per month. There is a further reduction to 0.33% per month after three months. There are similar reductions in the alphas across horizons. Clearly the predictability of ΔCVOL is not just a one-month affair, but it is concentrated within the next three months. The predictability of ΔPVOL is also longer than one month. The average return difference between the extreme ΔPVOL quintile portfolios controlling for ΔCVOL is –0.63% per month at the one-month horizon, and like the long-horizon return predictability pattern for the ΔCVOL portfolios, the predictability decreases by approximately half to –0.30% per month at the two-month horizon. After three months, the economic and statistical significance of ΔPVOL portfolios disappear.

In summary, the ΔCVOL and ΔPVOL predictability persists for at least three months, even longer in the case of ΔCVOL, but the strength of the predictability starts to halve after one month in both cases.

6. Joint Option and Equity Market Trading and Returns

Our findings rule out (noisy) rational expectations models of underlying and derivatives in incomplete markets such as Back (1993), Cao (1999), Buraschi and Jiltsov (2006), and many others. Despite being non-redundant securities, the prices of options in these models immediately adjust to any asymmetric or heterogeneous information possessed by agents, or the costs and incentives of acquiring such information, and thus these models predict that there is no predictability from option to stock markets or vice versa.[14]

Our results on the predictability of equity returns by option information may be consistent with a more recently developed strand of literature where investor demand for options can affect option prices. Bollen and Whaley (2004) build a demand-based option model for setting option prices and show that an excess of buyer-motivated traders cause option prices and implied volatility to rise. Building on this work, Garleanu, Pedersen and Poteshman (2009) develop an equilibrium model where the end-user demand of options affects the prices of options because risk-averse intermediaries who take the other side of end-users cannot perfectly hedge their option positions. They convincingly show that there is a strong empirical contemporaneous relation between option expensiveness and end-user demand for index and individual equity options.

The demand-based option pricing models of Bollen and Whaley (2004) and Garleanu, Pedersen and Poteshman (2009), however, do not directly predict that there should be lead-lag relations between option and stock markets. In addition to a demand effect in option markets, there must be a non-instantaneous response of the underlying stock market; the option market adjusts today and this predicts underlying stock prices next month. There are many models, both rational and behavioral that can explain this delayed reaction including information immobility (Van Nieuwerburgh and Veldkamp,

[14] Much of this literature focuses on the effects of introducing options into incomplete market economies. Because of asymmetric information, Back (1993) and Biais and Hillion (1994) show that introducing an option can cause underlying stock volatility to become stochastic and significantly increase. Most recently, Cao and Yang (2009) show that when options are introduced and when agents have differences of opinion, trading volumes reflect the differences of agents' opinion but all asset prices are formed as if a representative investor existed whose belief reflects the average beliefs across all investors. These issues are not empirically relevant for our results because we have focused on stock returns for which options already exist.

2009), limited attention (Hirshleifer, 2001), bounded rationality or limited updating of beliefs of agents in the stock market (Sargent, 1994), or the slow dissemination of news, or initial limited access to that news (see e.g. Hong and Stein, 1999). Of course, this assumes that the informed agents choose to place some trades in option markets – not all informed trades will be placed in option markets as Easley, O'Hara and Srinivas (1998) point out given the much greater liquidity of stock markets.

An investor who is well-informed that a stock is likely to increase, and who has chosen to invest in option markets, has a choice of buying a call, which increases call option volatilities, or shorting a put, which decreases put option volatilities. Consistent with informed trading, we conjecture that the predictability of call volatility innovations on future stock returns should be particularly pronounced when there is unusually high call volume. The same should hold true for the predictability of put volatility innovations.

Asymmetric Responses with Option Volume

We estimate cross-sectional regressions with option volatility innovations where the coefficients are allowed to exhibit asymmetry depending on the relative magnitudes of the call and put options trading volume:[15]

$$
\begin{aligned}
R_{i,t+1} &= \lambda_{0,t} + \lambda^{+}_{1,t}\Delta CVOL^{+}_{i,t} + \lambda^{-}_{1,t}\Delta CVOL^{-}_{i,t} + \varepsilon_{i,t+1} \\
R_{i,t+1} &= \lambda_{0,t} + \lambda^{+}_{2,t}\Delta PVOL^{+}_{i,t} + \lambda^{-}_{2,t}\Delta PVOL^{-}_{i,t} + \varepsilon_{i,t+1} \qquad (11)\\
R_{i,t+1} &= \lambda_{0,t} + \lambda^{+}_{1,t}\Delta CVOL^{+}_{i,t} + \lambda^{-}_{1,t}\Delta CVOL^{-}_{i,t} + \lambda^{+}_{2,t}\Delta PVOL^{+}_{i,t} + \lambda^{-}_{2,t}\Delta PVOL^{-}_{i,t} + \varepsilon_{i,t+1}
\end{aligned}
$$

where

$$\Delta CVOL^{+}_{i,t} = \begin{Bmatrix} \Delta CVOL_{i,t} & \text{if } \ln(\text{C/P Volume}) > Median \\ 0 & \text{otherwise} \end{Bmatrix},$$

$$\Delta CVOL^{-}_{i,t} = \begin{Bmatrix} \Delta CVOL_{i,t} & \text{if } \ln(\text{C/P Volume}) < Median \\ 0 & \text{otherwise} \end{Bmatrix},$$

$$\Delta PVOL^{+}_{i,t} = \begin{Bmatrix} \Delta PVOL_{i,t} & \text{if } \ln(\text{C/P Volume}) > Median \\ 0 & \text{otherwise} \end{Bmatrix},$$

$$\Delta PVOL^{-}_{i,t} = \begin{Bmatrix} \Delta PVOL_{i,t} & \text{if } \ln(\text{C/P Volume}) < Median \\ 0 & \text{otherwise} \end{Bmatrix}.$$

[15] A similar econometric specification is proposed by Bali (2000) to test the presence and significance of asymmetry in the conditional mean and conditional volatility of interest rate changes.

The regressions in equation (11) nest those in equation (5) when the predictability of option volatilities does not differ with option trading volume. For example, when $\lambda_1^+ = \lambda_1^-$ in the first regression in equation (11), we obtain our old regression

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\Delta CVOL_{i,t} + \varepsilon_{i,t+1},$$

because $\Delta CVOL_{i,t}^+ + \Delta CVOL_{i,t}^- = \Delta CVOL_{i,t}$.

We report the estimates of the asymmetric regressions in (11) in Table 9. The average slope coefficients on $\Delta CVOL_{i,t}^+$ and $\Delta CVOL_{i,t}^-$ are economically and statistically different from each other: $\lambda_1^+ = 2.61$ with a t-statistic of 3.29 and $\lambda_1^- = 0.73$ with a t-statistic of 0.98. The t-statistic from testing the equality of $\lambda_1^+ = \lambda_1^-$ is 2.57, suggesting the strongest predictability of call option volatility innovations is found when these are accompanied by greater than usual call option volume. This is consistent with informed investors buying call options, leading to increases in call volatilities which predict future stock price appreciation.

Similarly, we find the average slopes on $\Delta PVOL_{i,t}^+$ and $\Delta PVOL_{i,t}^-$ are economically and statistically different from each other as well; $\lambda_2^+ = 0.13$ with t-stat. = 0.20 and $\lambda_2^- = -1.92$ with a t-statistic of –3.28. We reject that $\lambda_2^+ = \lambda_2^-$ at the 95% level, which is consistent with investors with high-quality, sizeable information that stocks are trending down buy puts and the price discovery is occurring in put options with larger than usual trading volume. This causes increases in put option volatilities to lead next-month decreases in stock prices. Note that the effect of asymmetry is stronger on the put side than on the call side.

In regressions (3) and (4) in Table 9, we estimate the joint specifications with asymmetric responses of both call and put volatility innovations. The last regression specification controls for all factor risk and risk characteristics. Testing the effects produces weaker results, but the point estimates have the same sign as the call innovation and put innovation asymmetry regressions in the first two columns and economically indicate the same effect. The Wald statistic from testing the joint hypothesis is 5.03 with a *p*-value of 0.08, and when all controls are included it is 3.92 with a *p*-value of 0.14. Although statistically weaker than regressions (1) and (2), the point estimates in regression (4) on $\Delta CVOL_{i,t}^+$ and $\Delta CVOL_{i,t}^-$ are 4.13 and 3.30, respectively, implying a 25% higher impact of ΔCVOL when call option volatility innovations are accompanied by greater than usual call option volume. Similarly, the average slopes on $\Delta PVOL^{+}_{i,t}$ and $\Delta PVOL^{-}_{i,t}$ are –2.71 and –4.71, respectively, implying a 74% higher impact of ΔPVOL when put option volatility innovations are accompanied by larger than usual put option volume.

The results from these asymmetric regressions are consistent that the information contained in the call and put volatility innovations come from informed investors who have a high degree of precision of future movements of the stock price. Their actions move option prices today when they initiate trading in unusually high volumes, but their effects are not immediately priced into equity markets leading to stock market predictability.

7. Predicting the Cross Section of Implied Volatilities with Stock Returns

We finally examine the other direction of predictability and test if the cross section of stocks contains predictive information for the cross section of implied and realized volatilities. We are especially interested in the simplest of variables, the abnormal stock return (or alpha) which is analogous to the change in the implied volatility for options and is a crude proxy for news arrivals in stock markets.

7.1. Cross-Sectional Regressions

We examine the significance of information spillover from individual stocks to individual equity options based on the firm-level cross-sectional regressions:

$$\begin{aligned} \Delta CVOL_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} \cdot Alpha_{i,t} + Controls + \varepsilon_{i,t+1} \\ \Delta CVOL_{i,t+1} - \Delta PVOL_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} \cdot Alpha_{i,t} + Controls + \varepsilon_{i,t+1} \\ \Delta RVOL_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} \cdot Alpha_{i,t} + Controls + \varepsilon_{i,t+1}, \end{aligned} \tag{12}$$

where the dependent variables, ΔCVOL and ΔPVOL, denote the monthly changes in call and put implied volatilities for stock *i* over month *t* to *t*+1, and ΔRVOL denotes the monthly change in realized volatility of stock *i* over month *t* to *t*+1. Alpha is the abnormal return (or alpha) for stock *i* over the previous month *t* obtained from the CAPM model using a specification similar to regression (1).[16] The monthly alphas are computed by summing the daily idiosyncratic returns over the previous month. To test the significance of information flow from stock to options market, the cross-section of implied volatility changes over month *t*+1 are regressed on the abnormal returns of individual stocks in month *t*.

The first specification in equation (12) examines how call volatilities over the next month respond to stock returns over the previous month in the Alpha term. The second cross-sectional regression in

[16] Almost identical results are obtained using Fama-French (1993) alphas, as reported in the internet appendix.

equation (12) looks at how call volatilities move relative to put volatilities. Call and put volatilities tend to move in unison for the same firm. Predicting the spread between put and call implied volatilities, ΔPVOL – ΔCVOL, attempts to control for the common component in both call and put volatilities. The final regression in (12) predicts future firm-level realized volatilities in the cross section.

We deliberately do not use option returns as the dependent variable in equation (12). Option returns exhibit marked skewness and have pronounced non-linearities from dynamic leverage making statistical inference difficult (see, among others, Broadie, Chernov and Johannes, 2008; Chaudhri and Schroder, 2009). By focusing on implied volatilities we avoid many of these inference issues; our focus is on the cross section of implied volatilities. Our focus on cross-sectional predictability is also very different from most studies in the literature focusing on time-series relations like Christensen and Prabhala (1998) and Chernov (2007) who focus on the aggregate index level and Bollen and Whaley (2004) who examine time-series predictability of 20 individual options but focus only on net buying pressure. Our analysis is most similar to Goyal and Saretto (2009), but they examine actual option returns predicted by the difference between implied and realized volatilities.

Table 10 presents the Fama-MacBeth (1973) average slope coefficients and their Newey-West t-statistics in parentheses. Strikingly, many of the same stock risk characteristics that predict stock returns also predict implied volatilities. Options where the underlying stocks experienced high abnormal returns over the past month tend to increase their implied volatilities over the next month. Specifically, a 1% Alpha over the previous month increases call volatilities by 2.12%, on average, with a highly significant t-statistic of 3.88. High BETA this period predicts future decreases in implied volatilities and this is expected from the one-factor decomposition in equation (6). This goes beyond the finding of Duan and Wei (2009) who only show that current option levels, not future option volatility changes, are positively related to the proportion of systematic risk. High book-to-market stocks tend to exhibit decreases in implied volatilities next period with a coefficient of –0.16. There is a statistically significant momentum effect, but the coefficient is close to zero. The illiquidity effect is also very strong with a coefficient of 7.80 and t-statistic of 5.47. With the exception of SIZE, the standard stock characteristics have significant explanatory power in predicting option volatilities.

The predictability of the option volatilities by option characteristics is in line with the literature. Consistent with Goyal and Saretto (2009), options with large RVOL-IVOL tend to predict decreases in implied volatilities and so holding period returns on these options tend to be low. Increases in call and put open interest strongly predict future increases in call and put volatilities (cf. Roll, Schwartz and Subrahmanyam, 2009). Finally, changes in call (put) implied volatilities tend to be lower (higher) for options where the smile exhibits more pronounced negative skewness.

Table 10 interestingly shows that some variables differentially predict call and put volatilities. Note that call and put volatilities are correlated (Table 1 notes the cross sectional correlation is 0.57), but there is some independent movement. In the ΔCVOL – ΔPVOL column, Alpha and ILLIQ increase call volatilities more than put volatilities, while book-to-market decreases call volatilities less than put volatilities.

Finally, the last column of Table 10 shows that there is pronounced predictability in the cross section of realized volatilities. This predictability in realized volatilities is often the *opposite* to the predictability in implied volatilities. In particular, the Alpha coefficient in the ΔCVOL regression is 2.12, whereas the Alpha coefficient in the ΔRVOL regression is –19.22, which is approximately ten times larger in absolute value. High past stock returns predict increases in future implied volatilities that are not accompanied by increases in realized volatilities. In fact, future realized volatility tends to decline. In contrast, the effects for all the other stock characteristics are the same sign for both implied and realized volatilities.

7.2. Further Economic Investigation

To further investigate the predictability of option volatilities, we summarize the information in portfolios of option volatilities, similar to the portfolio returns constructed in Section 5. We focus on predictability by Alphas. Table 11 reports the results of averaged next-month implied volatilities where the portfolios are rebalanced at the start of every month ranking on a stock's Alpha over the previous month. Table 11 reports the same familiar results as Table 10 but now in a portfolio format. In Panel A, we use all stocks: options of stocks with low (high) past returns exhibit decreases (increases) in volatility, call and put volatilities both move but call volatilities move more, and realized volatilities tend to move in the opposite direction. Note that the differences in implied volatilities are across the extreme quintile portfolios are highly statistically significant in all cases. There are at least two economic channels explaining how short-term stock momentum can induce predictability in option volatilities: a behavioral and a rational story, and we examine each in turn.

Behavioral Explanations

Option volatilities may simply be mispriced in the sense of a behavioral asset pricing model. In particular, past high returns on a stock lead agents to become more uncertain of the future prospects of that stock, and so agents over-estimate future volatility. This is not reflected in realized fundamentals like future realized volatility. A behavioral model of this kind is developed by Barberis and Huang (2001), and

Goyal and Saretto (2009) appeal to this model to explain the positive returns on portfolios of option straddles that are long stocks with a large positive difference between historical and implied volatility and short stocks with a large negative difference between historical and implied volatility. In the Barberis and Huang model, agents are loss averse over gains and losses narrowly defined over individual stocks (through mental accounting). In their model, stocks with recent gains are perceived to be less risky and thus implied volatility declines.

In the Barberis and Huang model, the greater uncertainty of stock returns when stock prices have recently risen should be reflected in other uncertainty measures. Following Diether, Malloy, and Scherbina (2002), we take earnings dispersion of analysts, DISP, as a proxy for uncertainty about individual stock movements. We expect that for the Barberis and Huang story to hold, the change in DISP should also increase across the Low Alpha to High Alpha quintiles in Panel A, Table 11. This is not the case. The average change of DISP across the Low to High Alpha quintiles are 1.27, 0.42, –0.23, –0.36, and –0.21. That is, the ΔDISP goes in the opposite direction to the ΔCVOL numbers. This casts doubt on a behavioral over-reaction story for volatilities, at least as articulated by Barberis and Huang.

Rational Explanations

Can stock momentum predict option prices in a rational setting? Certainly not in complete markets, but when options are non-redundant then stock momentum may affect risk premiums, demand and supply, and option prices. A fully articulated model is beyond this article. First, the fact that many of the "usual suspects" forecast both the cross section of stock returns and option returns should not be surprising. Lo and Wang (1995) show that predictable returns do affect option prices because they affect estimates of volatility. An implication of this theory is that increases in predictability generally decrease option prices. Lo and Wang's argument is based on holding the unconditional time-series variance of a stock constant, and estimates of predictability change the conditional variance. Although Lo and Wang work with time-series predictability, the same concept is true with cross-sectional predictability which we examine. All else being equal, when the underlying stock return is more predictable, current option volatilities should decline. Since both the predictable component of stock returns and option volatilities are persistent processes, we should also expect that when stock returns are more predictable, the predictability of future option volatilities should decline.

To test this, we divide the sample into two groups of stocks based on the absolute residuals from the cross-sectional regressions of returns on the control variables in Table 3. Specifically, cross-sectional regressions are run with all variables in regression (3) in Table 3, without ΔCVOL and ΔPVOL. Since our objective is to determine whether the predictability of future volatilities is different for stocks with high and low predictability, we exclude ΔCVOL and ΔPVOL in the first-stage cross-sectional regressions to avoid interaction of the predictability of stock returns with the predictability of option volatilities. We divide the stock universe into two groups based on the median value of absolute residuals for each month. We label these two groups "High Cross-Sectional Predictability" and "Low Cross-Sectional Predictability". Panel B of Table 11 provides stronger predictability of future implied and realized volatilities for stocks with low cross-sectional predictability because the 5-1 differences in implied and realized volatilities across the extreme Alpha quintiles are economically and statistically larger for stocks with low absolute residuals. This result is consistent with the findings of Lo and Wang (1995): when stock returns are more predictable, the predictability of future volatilities declines.[17]

In demand-based option pricing models (see Bollen and Whaley, 2004; Garleanu, Pedersen and Poteshman, 2009), lagged stock returns could predict option volatilities because they forecast demand pressure of end users or unhedgeable components of option movements, which cannot be perfectly removed by option dealers. For the former, the pattern of option volumes is consistent with the forecasted changes in option volatilities: across the quintile option portfolios in Panel A, the change in option call volume increases, on average, from –113 to 561 as we move from the Low Alpha quintile to the High Alpha quintile. For the latter, we can examine how the predictability of option volatilities varies as the hedgeability of the underlying stock varies.

In Panel C of Table 11, we divide the universe into high and low volatility stocks based on the median level of realized volatility. Given basis risk, jump risk, and the inability to trade continuously, high volatility stocks are more unhedgeable than low volatility stocks. As shown in Panel C, we find stronger predictability for high volatility stocks because the 5-1 differences in implied and realized volatilities across the extreme Alpha quintiles are economically and statistically larger for high volatility stocks.

Second, we use the median ILLIQ measure of Amihud (2002) to split optionable stocks into two liquidity groups. Panel D of Table 11 considers liquid and illiquid stocks separately. We find that the predictability is less pronounced in liquid stocks: the ΔCVOL spread between the Low Alpha and High Alpha portfolios is smaller, there is less relative movement of call volatilities vs. put volatilities, and there is also less predictability of future realized volatility.

Finally, we divide stocks into two groups based on the median volatility uncertainty, where volatility uncertainty is measured by the variance of daily changes in call implied volatilities in a month. Stocks with high variance of ΔCVOL (or high volatility uncertainty) are harder to hedge, all else being

[17] We also obtain similar results when we measure stock return predictability using time-series predictability measures as opposed to cross-sectional measures in Table 11, Panel B. See the internet appendix.

equal, than stocks with low volatility uncertainty. Hence, Panel E of Table 11 shows that the predictability is more pronounced in stocks with high volatility uncertainty: the ΔCVOL, ΔCVOL – ΔPVOL, and ΔRVOL spreads between the Low Alpha and High Alpha portfolios are economically and statistically larger for stocks with higher volatility uncertainty. Overall, these results indicate that the predictability of implied and realized volatilities is related to the lack of hedgeability.

In Table 12, we break up the future call option volatilities into systematic and idiosyncratic components ($\Delta CVOL^{sys}$ and $\Delta CVOL^{idio}$) using real measure betas following Section 4.4. The systematic and idiosyncratic changes could exhibit different predictability because the systematic components are easier to hedge, given estimates of betas, in more liquid index markets. We find this is indeed the case. Table 12 shows that the strength and sign of predictability varies across the systematic and idiosyncratic components. The first column of Table 12 reports the cross-sectional regression of ΔCVOL from Table 10 for comparison. First, the positive coefficient on ΔCVOL is entirely due to stock idiosyncratic movements, but the negative sign on $\Delta CVOL^{sys}$ is statistically significant. This could be due to momentum predictability in index options found by Amin, Coval and Seyhun (2004). The BETA effect, as expected, is entirely systematic. On the other hand, the book-to-market effect is entirely stock specific. Finally, the effect of illiquidity is largely idiosyncratic in terms of the magnitude of the positive coefficient on $\Delta CVOL^{idio}$, although there is an opposite effect on $\Delta CVOL^{sys}$.

Long-Term Predictability

We end by examining long-term predictability of future call option volatility changes in Table 13 as a function of lagged stock Alphas. We follow our previous research design in the long-horizon portfolios in Section 5.3 and Table 8 and form Jegadeesh-Titman (1993) portfolios, except the portfolios are formed on call volatilities ranked by Alphas. Table 13 shows there is pronounced long-term volatility. The difference between High Alpha and Low Alpha call option volatility changes is 1.63% at the one-month horizon, which slowly dies off and remains at 0.55% at the six-month horizon. At the 12-month horizon (not reported in Table 13), the High Alpha minus Low Alpha call option volatility innovation difference is 0.32%. These results are interesting because it is well known that abnormal stock returns, or Alphas, have autocorrelations close to zero and have little persistence. In contrast, the strong persistence in option volatilities manifests itself in significant long-horizon predictability by stock market returns.

8. Conclusion

We document a remarkable ability of option volatilities to predict the cross section of stock returns and the stock returns to predict the cross section of option volatilities. In the direction of options to equity returns, stocks with past large innovations in call option implied volatilities positively predict future stock returns while stocks with previous large changes in put implied volatilities predict low stock returns over the next month. This cross-sectional predictability of stock returns from option volatility innovations is highly statistically significant both in cross-sectional regressions and portfolio returns. The effect is robust to the usual risk factors and characteristic controls, using control variables drawn from both equity and option markets, and appears in subsample periods including the most recent financial crisis. When quintile portfolios are created ranked on past first-differences in call volatilities, the spread in average returns and alphas between the first and fifth portfolios is approximately 1% per month. When accounting for the joint effects of call and put volatility innovations, the average raw and risk-adjusted return differences between the highest and lowest quintile portfolios of put volatility changes are in the range of 60 to 70 basis points per month.

Our results are consistent with demand-based option pricing models in which informed bullish investors with a high degree of confidence that the stock will appreciate choose to buy calls or sell puts. This causes large positive changes in call option volatilities and large negative changes in put option volatilities, which occurs contemporaneously with unusually high option volume. This information is not immediately reflected in the stock market leading to future stock price increases. Similarly, if put option sellers hold valuable, significant information that the stock will decline in the future, they will drive up the price of put options, or sell calls, and stocks with large changes in put volatilities will lead stock price depreciations. The predictive power of call and put volatility innovations is strongest when accompanied by greater than usual call (put) option volume. Supporting this explanation, we find that it is changes in the idiosyncratic, not systematic, components of implied volatilities that are driving the predictability, implying that investors first trading in option markets have better information about firm-specific news or events.

In the other direction of lagged equity returns to option volatilities, many variables that predict the cross section of stock returns also predict the cross section of implied volatilities. A particularly strong predictor is the lagged excess stock return. Options with underlying equities that have large price appreciations tend to increase in price over the next period. In particular, a 1% return relative to the CAPM over the previous month causes option implied volatilities to increase by around 2% and the increase in volatilities is larger for call options than for put options. At the same time, future realized volatilities are predicted to decline while option volatilities tend to rise. These effects are in excess of the co-movements of next-month option volatility changes with several lagged cross-sectional stock and option characteristics. The predictability of option volatilities is strongest for those options that exhibit the weakest underlying stock return predictability and are hardest to hedge. Both are consistent with rational sources of option return predictability.

Appendix: Estimating Betas from Option Information

We use the results in Bakshi, Kapadia, and Madan (2003) and Duan and Wei (2009) to obtain an estimate of a stock's market beta from the cross section of options. Bakshi, Kapadia, and Madan (2003) introduce a procedure to extract the volatility, skewness, and kurtosis of the risk-neutral return density from a group of out-of-the-money call and put options. Duan and Wei (2009) use the results in Bakshi, Kapadia, and Madan (2003) and define the risk-neutral market beta as a function of the risk-neutral skewness of individual stocks and the risk-neutral skewness of the market.

Let the τ-period continuously compounded return on the underlying asset i, S_i, be $R_{i,t}(\tau) = \ln[S_i(t+\tau)/S_i(\tau)]$. Let E_t^Q represent the expectation operator under the risk-neutral measure. The time-t price of a quadratic, cubic, and quartic payoff received at time $t+\tau$ can be written as $V_{i,t}(\tau) = E_t^Q[e^{-r\tau}R_{i,t}(\tau)^2]$, $W_{i,t}(\tau) = E_t^Q[e^{-r\tau}R_{i,t}(\tau)^3]$, and $X_{i,t}(\tau) = E_t^Q[e^{-r\tau}R_{i,t}(\tau)^4]$, respectively, where r is the constant risk-free rate.

Bakshi, Kapadia, and Madan (2003) show that the τ-period risk-neutral variance and skewness are

$$Var_{i,t}^Q(\tau) = e^{r\tau}V_{i,t}(\tau) - \mu_{i,t}(\tau)^2 \tag{A.1}$$

$$Skew_{i,t}^Q(\tau) = \frac{e^{r\tau}W_{i,t}(\tau) - 3\mu_{i,t}(\tau)e^{r\tau}V_{i,t}(\tau) + 2\mu_{i,t}(\tau)^3}{\left[e^{r\tau}V_{i,t}(\tau) - \mu_{i,t}(\tau)^2\right]^{3/2}} \tag{A.2}$$

The expressions $V_{i,t}(\tau)$, $W_{i,t}(\tau)$, and $X_{i,t}(\tau)$ are given by:

$$V_{i,t}(\tau) = \int_{S_{i,t}}^{\infty} \frac{2(1-\ln(K_i/S_{i,t}))}{K_i^2} C_{i,t}(\tau;K_i)dK_i + \int_0^{S_{i,t}} \frac{2(1-\ln(K_i/S_{i,t}))}{K_i^2} P_{i,t}(\tau;K_i)dK_i \tag{A.3}$$

$$\begin{aligned} W_{i,t}(\tau) = &\int_{S_{i,t}}^{\infty} \frac{6\ln(K_i/S_{i,t}) - 3[\ln(K_i/S_{i,t})]^2}{K_i^2} C_{i,t}(\tau;K_i)dK_i \\ &+ \int_0^{S_{i,t}} \frac{6\ln(K_i/S_{i,t}) - 3[\ln(K_i/S_{i,t})]^2}{K_i^2} P_{i,t}(\tau;K_i)dK_i \end{aligned} \tag{A.4}$$

$$\begin{aligned} X_{i,t}(\tau) = &\int_{S_{i,t}}^{\infty} \frac{12[\ln(K_i/S_{i,t})]^2 - 4[\ln(K_i/S_{i,t})]^3}{K_i^2} C_{i,t}(\tau;K_i)dK_i \\ &+ \int_0^{S_{i,t}} \frac{12[\ln(K_i/S_{i,t})]^2 - 4[\ln(K_i/S_{i,t})]^3}{K_i^2} P_{i,t}(\tau;K_i)dK_i \end{aligned} \tag{A.5}$$

$$\mu_{i,t}(\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}V_{i,t}(\tau)}{2} - \frac{e^{r\tau}W_{i,t}(\tau)}{6} - \frac{e^{r\tau}X_{i,t}(\tau)}{24} \tag{A.6}$$

where $C_{i,t}(\tau;K_i)$ and $P_{i,t}(\tau;K_i)$ are the time-*t* prices of European call and put options written on the underlying stock $S_{i,t}$ with a strike price K_i and expiration date of τ. We follow Dennis and Mayhew (2002) and use the trapezoidal approximation to compute the integrals in equations (A.1) and (A.2) for out-of-the-money call and put options across different strike prices and use the Volatility Surface data on standardized options with the three-month T-bill return for the risk-free rate.

Duan and Wei (2009) show that the risk-neutral skewness of an individual stock, $Skew_{i,t}^{Q}(\tau)$, is related to the risk-neutral skewness of the market, $Skew_{m,t}^{Q}(\tau)$, through the relation

$$Skew_{i,t}^{Q}(\tau) = \beta_i^{3/2}(\tau) Skew_{m,t}^{Q}, \tag{A.7}$$

where $Skew_{i,t}^{Q}(\tau)$ and $Skew_{m,t}^{Q}(\tau)$ are estimated using equation (A.2). In our empirical analyses, we use Volatility Surface standardized call and put options with τ=30 days to maturity to estimate the stock beta from equation (A.7). We use Volatility Surface data on the S&P500 index to compute the risk-neutral market skewness.

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Table 1. Descriptive Statistics of Implied Volatilities

Panel A presents the average number of stocks per month for each year from 1996 to 2008. Average and standard deviation of the monthly call and put implied volatilities (CVOL, PVOL) are reported for each year from 1996 to 2008. The last row presents the overall averages. The annualized implied volatilities are obtained from the Volatility Surface at OptionMetrics and cover the period from January 1996 to September 2008. Panel B reports the average firm-level cross-correlations of the levels and changes in implied volatilities, the levels and changes in realized volatility, and time-series and cross-sectional shocks to implied volatilities.

Panel A. Summary Statistics for the Call and Put Implied Volatilities

		CVOL		PVOL	
Date	# of stocks	Average	Stdev	Average	Stdev
1996	1292	43.17	21.22	44.04	20.81
1997	1556	45.64	20.79	46.23	20.37
1998	1792	51.97	22.61	52.32	21.85
1999	1866	57.87	24.44	58.59	24.17
2000	1675	71.13	31.68	72.19	31.70
2001	1587	61.50	27.73	63.43	29.05
2002	1658	54.62	24.00	56.00	26.29
2003	1630	43.00	18.70	43.54	18.82
2004	1744	38.57	17.94	39.34	18.61
2005	1902	36.92	19.15	37.98	19.96
2006	2017	37.25	17.59	37.95	17.78
2007	2161	39.78	19.27	40.51	19.47
2008	2175	53.52	23.27	54.93	24.78
Average	1774	48.84	22.18	49.77	22.59

Table 1 (continued)

Panel B. Average Firm-Level Correlations

	CVOL	PVOL	ΔCVOL	ΔPVOL	RVOL	ΔRVOL	$CVOL_{ts}^{shock}$	$PVOL_{ts}^{shock}$	$CVOL_{cs}^{shock}$	$PVOL_{cs}^{shock}$
CVOL	1									
PVOL	0.92	1								
ΔCVOL	0.29	0.16	1							
ΔPVOL	0.17	0.29	0.57	1						
RVOL	0.67	0.67	0.04	0.05	1					
ΔRVOL	0.03	0.04	0.10	0.11	0.48	1				
$CVOL_{ts}^{shock}$	0.37	0.23	0.83	0.49	0.10	0.10	1			
$PVOL_{ts}^{shock}$	0.22	0.35	0.50	0.81	0.10	0.11	0.63	1		
$CVOL_{cs}^{shock}$	0.51	0.38	0.95	0.54	0.21	0.09	0.83	0.49	1	
$PVOL_{cs}^{shock}$	0.39	0.52	0.54	0.95	0.22	0.10	0.50	0.81	0.60	1

Table 2. Predicting Equity Returns by Levels and Changes in Implied Volatilities

This table presents the average slope coefficients and their Newey-West (1987) adjusted t-statistics in parentheses from the firm-level Fama-MacBeth (1973) cross-sectional regressions. The one-month ahead returns of individual stocks are regressed on the level and changes in call implied volatility, put implied volatility, and realized volatility for the full sample period of January 1996 to September 2008 (Panel A) as well as several subsample periods (Panel B). The call and put implied volatilities are obtained from standardized at-the-money options with 30 days to maturity.

Panel A. Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CVOL	–0.9447							
	(–0.77)							
PVOL		–1.6971						
		(–1.41)						
RVOL			–1.3239					
			(–1.53)					
ΔCVOL				1.8741			3.5993	3.6087
				(2.90)			(5.02)	(5.16)
ΔPVOL					–0.9484		–2.8635	–2.7490
					(–2.09)		(–5.32)	(–5.11)
ΔRVOL						0.0011		0.0002
						(0.30)		(0.05)

Panel B. Subsamples

	Jan 1996– Sep 2008	Jan 1996– Dec 2001	Jan 2002– Sep 2008	Jan 2008– Sep 2008
ΔCVOL	3.5993	4.3520	2.9567	2.5043
	(5.02)	(4.71)	(2.92)	(2.32)
ΔPVOL	–2.8635	–2.5955	–3.0922	–2.2809
	(–5.32)	(–3.79)	(–3.65)	(–4.28)

Table 3. Predicting Equity Returns by First Differences in Implied Volatilities and Other Predictors

This table presents the firm-level cross-sectional regressions in equation (5) of equity returns on the monthly changes in call and put implied volatilities (ΔCVOL and ΔPVOL, respectively) after controlling for market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), illiquidity (ILLIQ), short-term reversal (REV), realized stock return volatility (RVOL), the log call-put ratio of option trading volume (C/P Volume), the log ratio of call-put open interest (C/P OI), the realized-implied volatility spread (RVOL-IVOL), and the risk-neutral measure of skewness (QSKEW). The results are presented for at-the-money 30-day options. The average slope coefficients and their Newey-West t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)
ΔCVOL	1.4888		3.6494	3.4269
	(2.41)		(4.83)	(4.58)
ΔPVOL		-2.0704	-3.8445	-4.1216
		(-3.94)	(-5.29)	(-5.72)
BETA	0.1314	0.1114	0.1208	0.0154
	(0.40)	(0.34)	(0.37)	(0.04)
SIZE	-0.1615	-0.1488	-0.1541	-0.0800
	(-1.40)	(-1.30)	(-1.34)	(-0.62)
BM	0.0605	0.0603	0.0587	0.0850
	(0.75)	(0.75)	(0.73)	(1.00)
MOM	0.0032	0.0034	0.0032	0.0029
	(1.52)	(1.59)	(1.53)	(1.35)
ILLIQ	0.5984	0.6933	0.6701	0.2093
	(0.28)	(0.32)	(0.31)	(0.10)
REV	-0.0128	-0.0179	-0.0144	-0.0146
	(-1.45)	(-1.92)	(-1.61)	(-1.62)
RVOL	-1.1773	-0.9502	-1.0593	
	(-2.71)	(-2.23)	(-2.44)	
C/P Volume	0.1760	0.3583	0.2705	0.2781
	(1.43)	(2.66)	(2.10)	(2.16)
C/P OI	-0.0139	-0.0167	-0.0157	0.0069
	(-0.26)	(-0.32)	(-0.30)	(0.12)
RVOL-IVOL				-0.4024
				(-1.14)
QSKEW	-3.3362	-3.9395	-3.0845	-3.0545
	(-4.85)	(-5.65)	(-4.65)	(-4.50)

Table 4. Predicting Equity Returns by Time-Series and Cross-Sectional Implied Volatility Innovations

This table presents the average slope coefficients and their Newey-West adjusted t-statistics in parentheses from the firm-level Fama-MacBeth cross-sectional regressions in equation (5) for the sample period of January 1996 to September 2008. The one-month ahead returns of individual stocks are regressed on the monthly innovations in call and put implied volatilities obtained from at-the-money options with 30 days to maturity. In the left panel, the monthly innovations in implied volatilities are generated based on the firm-level cross-sectional regressions of implied volatilities on their one-month lagged values estimated for each month in our sample (see equation (4)). In right panel, the monthly innovations in implied volatilities are generated based on the time-series AR(1) model estimated for each firm using the past two years of monthly data (see equation (3)).

	Cross-Sectional Measures of Volatility Innovations				Time-Series Measures of Volatility Innovations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CVOL^{shock}$	1.4664		3.7809	3.4509	1.5893		5.0686	4.8918
	(2.20)		(4.72)	(4.18)	(1.85)		(4.17)	(4.08)
$PVOL^{shock}$		-2.2832	-4.1359	-4.4268		-2.0864	-5.2705	-5.4560
		(-4.20)	(-5.69)	(-6.20)		(-2.58)	(-4.39)	(-4.44)
BETA	0.1157	0.1228	0.1153	0.0049	0.1200	0.0962	0.0985	0.0645
	(0.35)	(0.37)	(0.35)	(0.01)	(0.29)	(0.21)	(0.24)	(0.14)
SIZE	-0.1489	-0.1537	-0.1473	-0.0716	-0.2475	-0.2261	-0.2359	-0.2110
	(-1.30)	(-1.33)	(-1.29)	(-0.56)	(-2.27)	(-1.87)	(-2.16)	(-1.90)
BM	0.0637	0.0611	0.0619	0.0885	-0.0497	-0.0421	-0.0467	-0.0266
	(0.79)	(0.76)	(0.77)	(1.03)	(-0.48)	(-0.25)	(-0.45)	(-0.25)
MOM	0.0032	0.0034	0.0032	0.0029	0.0040	0.0039	0.0039	0.0039
	(1.52)	(1.58)	(1.52)	(1.37)	(1.39)	(1.31)	(1.35)	(1.32)
ILLIQ	0.6233	0.7640	0.7131	0.2532	-1.3981	-1.3806	-1.5772	-1.4539
	(0.29)	(0.35)	(0.33)	(0.12)	(-0.61)	(-0.52)	(-0.69)	(-0.63)
REV	-0.0130	-0.0181	-0.0147	-0.0150	-0.0106	-0.0157	-0.0121	-0.0115
	(-1.47)	(-1.95)	(-1.64)	(-1.65)	(-1.11)	(-1.47)	(-1.26)	(-1.19)
RVOL	-1.2221	-0.9280	-1.0770		-0.5818	-0.2949	-0.4516	
	(-2.85)	(-2.18)	(-2.50)		(-1.17)	(0.30)	(-0.94)	
C/P Volume	0.1742	0.3661	0.2764	0.2922	0.0252	0.0184	0.0191	0.0161
	(1.44)	(2.74)	(2.17)	(2.29)	(0.50)	(0.74)	(0.38)	(0.32)
C/P OI	-0.0092	-0.0184	-0.0133	0.0107	0.0437	0.0375	0.0413	0.0476
	(-0.17)	(-0.35)	(-0.25)	(0.19)	(0.73)	(-1.07)	(0.70)	(0.79)
RVOL-IVOL				-0.4117				-0.4235
				(-1.17)				(-1.02)
QSKEW	-3.3615	-3.9798	-3.0980	-3.1262	-3.0585	-3.4513	-2.5643	-2.5533
	(-4.85)	(-5.72)	(-4.70)	(-4.62)	(-3.54)	(-3.92)	(-2.91)	(-3.00)

Table 5. Predicting Returns by Systematic and Idiosyncratic Volatility Shocks

This table presents the average slope coefficients and their Newey-West adjusted t-statistics in parentheses from the firm-level Fama-MacBeth cross-sectional regressions in equation (5) for the sample period of January 1996 to September 2008. The one-month ahead returns of individual stocks are regressed on the systematic and idiosyncratic components of the changes in call and put implied volatilities and the control variables. $\Delta CVOL^{sys}$, $\Delta CVOL^{idio}$, $\Delta PVOL^{sys}$, and $\Delta PVOL^{idio}$ are defined in equation (7) and are obtained from the physical measure of market beta (the left panel) and from the risk-neutral measure of market beta (the right panel). The results are presented for at-the-money call and put options with 30 days to maturity.

	Physical Measure of Market Beta				Risk-Neutral Measure of Market Beta			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta CVOL^{sys}$	-0.5772	-0.5894			0.3826	0.3376		
	(-0.93)	(-0.95)			(0.38)	(0.34)		
$\Delta CVOL^{idio}$	1.7816	1.7694	1.7816	1.7694	1.5310	1.5142	1.5310	1.5142
	(3.13)	(3.10)	(3.13)	(3.10)	(3.11)	(3.06)	(3.11)	(3.06)
$\Delta PVOL^{sys}$			-0.6557	-0.6699			0.3822	0.3399
			(-1.02)	(-1.04)			(0.39)	(0.35)
$\Delta PVOL^{idio}$	-2.3514	-2.3660	-2.3514	-2.3660	-2.3034	-2.3190	-2.3034	-2.3190
	(-4.09)	(-4.13)	(-4.09)	(-4.13)	(-3.85)	(-3.88)	(-3.85)	(-3.88)
BETA	0.0428	0.0394	0.0568	0.0535	0.0461	0.0504	0.0404	0.0445
	(0.22)	(0.20)	(0.29)	(0.27)	(0.19)	(0.21)	(0.17)	(0.19)
SIZE	-0.1328	-0.1286	-0.1328	-0.1286	-0.1258	-0.1201	-0.1258	-0.1201
	(-1.46)	(-1.40)	(-1.46)	(-1.40)	(-1.37)	(-1.30)	(-1.37)	(-1.30)
BM	0.0198	0.0228	0.0198	0.0228	0.0307	0.0352	0.0307	0.0352
	(0.18)	(0.20)	(0.18)	(0.20)	(0.25)	(0.28)	(0.25)	(0.28)
MOM	0.3354	0.3319	0.3354	0.3319	0.3544	0.3521	0.3544	0.3521
	(1.44)	(1.42)	(1.44)	(1.42)	(1.48)	(1.46)	(1.48)	(1.46)
ILLIQ	0.0082	0.0007	0.0082	0.0007	0.1748	0.1691	0.1748	0.1691
	(0.04)	(0.00)	(0.04)	(0.00)	(0.84)	(0.82)	(0.84)	(0.82)
REV	-0.0184	-0.0183	-0.0184	-0.0183	-0.0185	-0.0183	-0.0185	-0.0183
	(-2.05)	(-2.03)	(-2.05)	(-2.03)	(-2.15)	(-2.13)	(-2.15)	(-2.13)
RVOL	-0.0618		-0.0618		-0.0863		-0.0863	
	(-2.06)		(-2.06)		(-2.39)		(-2.39)	
C/P Volume	0.0497	0.0497	0.0497	0.0497	0.0599	0.0598	0.0599	0.0598
	(1.04)	(1.04)	(1.04)	(1.04)	(1.23)	(1.23)	(1.23)	(1.23)
C/P OI	0.0937	0.0935	0.0937	0.0935	0.0652	0.0650	0.0652	0.0650
	(1.47)	(1.47)	(1.47)	(1.47)	(1.03)	(1.03)	(1.03)	(1.03)
RVOL-IVOL		-0.0606		-0.0606		-0.0860		-0.0860
		(-2.05)		(-2.05)		(-2.40)		(-2.40)
QSKEW	-3.4094	-3.3948	-3.4094	-3.3948	-3.0371	-3.0165	-3.0371	-3.0165
	(-5.63)	(-5.61)	(-5.63)	(-5.61)	(-5.11)	(-5.07)	(-5.11)	(-5.07)

Table 6. Portfolios Ranked on Implied Call and Put Volatility Innovations

In Panel A, Portfolio 1 (Low ΔCVOL) contains stocks with the lowest monthly changes in call implied volatilities in the previous month and Portfolio 5 (High ΔCVOL) includes stocks with the highest monthly changes in call implied volatilities in the previous month. For each quintile of ΔCVOL, the columns report the average raw returns, the CAPM and FF3 alphas, and the average returns in excess of the size and book-to-market matched benchmark portfolios (characteristic-control) following Daniel and Titman (1997). The row "5-1 Diff." reports the difference in average raw and risk-adjusted returns between the High ΔCVOL and Low ΔCVOL quintiles. Panel B reports the corresponding results from the univariate quintile portfolios of ΔPVOL. In Panel C, quintile portfolios are first formed by sorting the optionable stocks based on ΔPVOL. Then, within each ΔPVOL quintile, stocks are sorted into quintile portfolios ranked based on the monthly changes in call implied volatilities (ΔCVOL) so that ΔCVOL1 (ΔCVOL5) contains stocks with the lowest (highest) ΔCVOL. The column labeled "ΔCVOL5 – ΔCVOL1" shows the average raw return difference between High ΔCVOL (ΔCVOL5) and Low ΔCVOL (ΔCVOL1) portfolios within each ΔPVOL quintile. Panel D performs a similar dependent sort procedure but first sequentially sorts on ΔCVOL and then on ΔPVOL. The column labeled "ΔPVOL5 – ΔPVOL1" shows the average raw return difference between ΔPVOL5 and ΔPVOL1 portfolios within each ΔCVOL quintile. In Panels C and D, "Return Diff." reports the average raw return difference between ΔCVOL5 (ΔPVOL5) and ΔCVOL1 (ΔPVOL1) after controlling for ΔPVOL (ΔCVOL). "Alpha Diff." reports the 5-1 differences in the FF3 alphas. The monthly change in option trading volume and the monthly change in open interest are reported. Newey-West t-statistics are given in parentheses.

Panel A. Portfolios Ranked on ΔCVOL

	Return	CAPM Alpha	FF3 Alpha	Characteristic-Control
Low ΔCVOL	0.10	–0.53	–0.69	–0.43
2	0.50	–0.07	–0.32	–0.14
3	0.80	0.25	–0.04	0.08
4	1.00	0.42	0.15	0.22
High ΔCVOL	1.07	0.41	0.21	0.27
5-1 Diff.	0.97	0.94	0.90	0.71
t-stat.	(3.37)	(3.59)	(3.37)	(3.34)

Panel B. Portfolios Ranked on ΔPVOL

	Return	CAPM Alpha	FF3 Alpha	Characteristic-Control
Low ΔPVOL	0.60	–0.04	–0.19	–0.01
2	0.72	0.14	–0.10	0.03
3	0.89	0.34	0.06	0.15
4	0.84	0.26	–0.01	0.11
High ΔPVOL	0.45	–0.21	–0.41	–0.29
5-1 Diff.	–0.15	–0.17	–0.22	–0.28
t-stat.	(–0.62)	(–0.93)	(–1.29)	(–2.51)

Table 6 (continued)

Panel C. Portfolios Ranked First on ΔPVOL and then on ΔCVOL

	ΔCVOL1	ΔCVOL2	ΔCVOL3	ΔCVOL4	ΔCVOL5	ΔCVOL5 – ΔCVOL1
ΔPVOL1	–0.10	0.45	0.60	0.75	1.24	1.34
						(4.17)
ΔPVOL2	0.31	0.37	0.54	0.86	1.51	1.19
						(4.40)
ΔPVOL3	0.41	0.63	1.03	0.97	1.42	1.01
						(4.11)
ΔPVOL4	0.20	0.80	0.95	1.00	1.21	1.01
						(4.26)
ΔPVOL5	–0.45	0.45	0.58	1.01	0.63	1.08
						(2.80)
$\Delta Volume^C$	–24.22	–10.28	–7.78	32.39	96.63	
ΔOI^C	26.65	67.69	81.71	105.64	144.93	
					Return Diff.	1.13
						(5.39)
					FF3 Alpha Diff.	1.12
						(4.95)

Panel D. Portfolios Ranked First on ΔCVOL and then on ΔPVOL

	ΔPVOL1	ΔPVOL2	ΔPVOL3	ΔPVOL4	ΔPVOL5	ΔPVOL5 – ΔPVOL1
ΔCVOL1	0.27	0.33	0.19	0.06	–0.31	–0.58
						(–2.04)
ΔCVOL2	0.53	0.55	0.55	0.48	0.37	–0.16
						(–0.73)
ΔCVOL3	0.91	0.86	0.82	0.93	0.51	–0.40
						(–1.86)
ΔCVOL4	1.22	1.22	1.00	0.94	0.63	–0.59
						(–3.28)
ΔCVOL5	1.60	1.30	1.15	1.13	0.16	–1.44
						(–4.76)
$\Delta Volume^P$	–26.27	–9.58	16.71	34.37	98.55	
ΔOI^P	2.27	15.64	52.95	66.63	72.89	
					Return Diff.	–0.63
						(–4.81)
					FF3 Alpha Diff.	–0.68
						(–5.51)

Table 7. Portfolios of Small and Large Stocks Ranked on Implied Call and Put Volatility Innovations

This table reports the differences in average raw returns and FF3 Alphas performing dependent sorts in large and small stocks. First, optionable stocks are sorted into two groups based on their market capitalization (Small vs. Big). Within the Small stock group, quintile portfolios are formed based on ΔPVOL. Then, within each ΔPVOL quintile, small stocks are sorted into quintile portfolios ranked based on the monthly changes in call implied volatilities (ΔCVOL) so that ΔCVOL1 (ΔCVOL5) contains small stocks with the lowest (highest) ΔCVOL. We take the difference in returns or FF3 Alphas between quintile 1 and 5 for each ΔCVOL portfolio and then average the returns or FF3 Alphas across the ΔPVOL quintiles. This produces the return and FF3 Alpha differences "Ranking on ΔCVOL Controlling for ΔPVOL". We perform dependent sorts the opposite way, that is first ranking on ΔCVOL and then within each ΔCVOL quintile, sorting stocks into quintile portfolios ranked based on the monthly changes in put implied volatilities, and then perform the same procedure for average return differences and FF3 alphas to compute the numbers for "Ranking on ΔPVOL Controlling for ΔCVOL". This procedure is done separately on Small and Big stocks. Newey-West t-statistics are reported in parentheses.

		Return Difference	FF3 Alpha Difference
Small Stocks	Ranking on ΔCVOL	1.45	1.44
	Controlling for ΔPVOL	(4.76)	(4.32)
	Ranking on ΔPVOL	–0.87	–0.93
	Controlling for ΔCVOL	(–4.80)	(–4.71)
Big Stocks	Ranking on ΔCVOL	0.61	0.59
	Controlling for ΔPVOL	(3.57)	(3.61)
	Ranking on ΔPVOL	–0.37	–0.46
	Controlling for ΔCVOL	(–2.82)	(–3.32)

Table 8. Long-Term Predictability

This table presents the bivariate portfolios of ΔCVOL and ΔPVOL based on the dependent sorts. We hold these portfolios for 1 to 6 months and rebalance them monthly. In the first panel, quintile portfolios are first formed by sorting the optionable stocks based on ΔPVOL. Then, within each ΔPVOL quintile, stocks are sorted into quintile portfolios ranked based on the monthly changes in call implied volatilities (ΔCVOL) so that ΔCVOL1 (ΔCVOL5) contains stocks with the lowest (highest) ΔCVOL. The second panel performs a similar dependent sort procedure but first sequentially sorts on ΔCVOL and then on ΔPVOL. The first panel reports the 1-month to 6-month ahead average raw and risk-adjusted return differences between High ΔCVOL and Low ΔCVOL portfolios after controlling for ΔPVOL. The second panel reports the 1-month to 6-month ahead average raw and risk-adjusted return differences between High ΔPVOL and Low ΔPVOL portfolios after controlling for ΔCVOL. Newey-West t-statistics are reported in parentheses.

	1-month	2-month	3-month	4-month	5-month	6-month
Ranking on ΔCVOL Controlling for ΔPVOL						
Average Return Diff.	1.13	0.49	0.33	0.21	0.20	0.13
	(5.39)	(4.56)	(3.48)	(3.23)	(3.43)	(2.31)
FF3 Alpha Diff.	1.12	0.48	0.34	0.23	0.21	0.14
	(4.95)	(3.95)	(3.02)	(2.59)	(2.73)	(1.90)
Ranking on ΔPVOL Controlling for ΔCVOL						
Average Return Diff.	–0.63	–0.30	–0.18	–0.08	–0.04	–0.11
	(–4.81)	(–4.38)	(–3.18)	(–1.54)	(–1.01)	(–2.55)
FF3 Alpha Diff.	–0.68	–0.31	–0.19	–0.06	–0.03	–0.10
	(–5.51)	(–4.94)	(–3.21)	(–0.97)	(–0.59)	(–2.42)

Table 9. Predicting Equity Returns by Asymmetric Volatility Shocks

This table presents the average slope coefficients and their Newey-West adjusted t-statistics in parentheses from the firm-level Fama-MacBeth cross-sectional regressions in equation (11) for the sample period of January 1996 to September 2008. The one-month ahead returns of individual stocks are regressed on the asymmetric call and put implied volatility shocks. $\Delta CVOL^{+}$, $\Delta CVOL^{-}$, $\Delta PVOL^{+}$, $\Delta PVOL^{-}$ are defined below equation (11). The results are presented for at-the-money call and put options with 30 days to maturity.

	(1)	(2)	(3)	(4)
$\Delta CVOL^{+}$	2.6122		4.0445	4.1312
	(3.29)		(4.86)	(4.35)
$\Delta CVOL^{-}$	0.7276		3.3230	3.3041
	(0.98)		(3.83)	(3.99)
$\Delta PVOL^{+}$		0.1286	-2.1943	-2.7095
		(-0.20)	(-3.39)	(-3.34)
$\Delta PVOL^{-}$		-1.9241	-3.7909	-4.7104
		(-3.28)	(-5.14)	(-4.55)
$\lambda_1^{+} = \lambda_1^{-}$	$t = 2.57$			
$\lambda_2^{+} = \lambda_2^{-}$		$t = 2.90$		
$\lambda_1^{+} = \lambda_1^{-}$, $\lambda_2^{+} = \lambda_2^{-}$			Wald = 5.03 ($p = 0.08$)	Wald = 3.92 ($p = 0.14$)
Other Controls	No	No	No	Yes

Table 10. Predicting the Cross Section of Implied and Realized Volatilities

This table presents coefficients from the cross-sectional regression in equation (12) which predict changes in options' implied volatilities and the changes in realized volatility. The daily alphas are estimated based on the CAPM using daily return observations over the previous month. The monthly Alphas are calculated by summing the daily alphas in a month. The dependent variables are, respectively, the next-month changes in call volatilities, ΔCVOL, the change in call volatilities relative to put volatilities, ΔCVOL – ΔPVOL, and the change in realized volatilities, ΔRVOL. The average slope coefficients and their Newey-West t-statistics from the firm-level cross-sectional regressions are reported. The control variables include market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), illiquidity (ILLIQ), realized-implied volatility spread (RVOL-IVOL), change in the call open interest (ΔOI^{C}), change in the put open interest (ΔOI^{P}), and the risk-neutral skewness (QSKEW). Newey-West t-statistics are given in parentheses. The sample period is from January 1996 to September 2008.

	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL
ALPHA	2.1225	1.9230	–19.2191
	(3.88)	(4.26)	(–9.83)
BETA	–0.5192	0.0432	–3.6055
	(–3.36)	(0.46)	(–6.70)
SIZE	0.0651	0.0632	–0.7928
	(1.60)	(1.72)	(–10.49)
BM	–0.1551	–0.0832	–0.1512
	(–3.83)	(–3.59)	(–1.52)
MOM	0.0037	0.0002	0.0017
	(3.57)	(0.42)	(0.72)
ILLIQ	7.7977	2.8659	15.8027
	(5.47)	(1.84)	(4.64)
RVOL-IVOL	9.3746	–1.3348	86.4431
	(10.26)	(–2.29)	(99.57)
ΔOI^{C}	–1.0207	–0.2072	–3.1119
	(–11.03)	(–2.63)	(–18.53)
ΔOI^{P}	–0.5345	–0.0043	–1.5600
	(–10.22)	(–0.10)	(–15.47)
QSKEW	24.031	30.145	–8.5087
	(11.64)	(9.55)	(–5.31)

Table 11. Portfolio Level Analyses for Predicting Implied and Realized Volatilities

This table presents portfolio level results for the predictive power of abnormal returns of individual stocks (CAPM alphas) for the future changes in implied and realized volatilities. The monthly alphas are calculated by summing the daily alphas in a month. The daily alphas are estimated based on the CAPM using daily return observations over the previous month. Quintile portfolios are formed based on the monthly CAPM alphas and then the average values are reported for the next-month changes in call volatilities (ΔCVOL), the next-month change in call volatilities relative to put volatilities (ΔCVOL – ΔPVOL), and the next-month change in realized volatilities (ΔRVOL). Panel A reports results for all optionable stocks. Panel B shows results for stocks with high and low cross-sectional stock return predictability separately, where predictability is measured by the absolute value of residuals from the first stage cross-sectional regressions using the same predictors in Table 3 without ΔCVOL or ΔPVOL. Panel C provides results for stocks with high volatility and low volatility separately, where volatility of individual stocks is measured by the monthly realized volatility. Panel D shows results for Liquid and Illiquid stocks separately, where liquidity of individual stocks are determined by Amihud's (2002) ILLIQ measure. Panel E presents results for stocks with high volatility uncertainty and low volatility uncertainty separately, where volatility uncertainty is proxied by the variance of daily changes in call implied volatilities in a month. Newey-West t-statistics are given in parentheses. The sample period is from January 1996 to September 2008.

Panel A. All Stocks

	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL
Low Alpha	–0.84	–0.69	0.76
2	–0.22	–0.23	3.41
3	0.22	0.08	2.20
4	0.51	0.17	0.77
High Alpha	0.79	0.51	–6.84
5-1 Diff.	1.63	1.20	–7.60
t-stat.	(7.75)	(6.33)	(–11.98)

Panel B. High Cross-Sectional Predictability vs. Low Cross-Sectional Predictability

	Stocks with Low Cross-Sectional Predictability			Stocks with High Cross-Sectional Predictability		
	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL
Low Alpha	–0.64	–0.87	1.23	–1.21	–0.52	0.54
2	0.01	–0.25	4.03	–0.38	–0.25	2.99
3	0.55	0.16	2.71	–0.06	–0.01	1.82
4	0.93	0.28	0.86	0.23	0.16	0.66
High Alpha	1.04	0.66	–7.94	0.35	0.37	–6.45
5-1 Diff.	1.68	1.53	–9.17	1.56	0.88	–6.99
t-stat.	(7.71)	(7.37)	(–11.96)	(7.50)	(4.48)	(–12.06)

Table 11 (continued)

Panel C. High Volatility vs. Low Volatility

	Low Volatility Stocks			High Volatility Stocks		
	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL
Low Alpha	–1.09	–0.42	–7.03	–0.91	–0.80	–3.66
2	–0.39	–0.14	–1.76	0.09	–0.40	10.05
3	–0.01	0.05	–1.84	0.75	0.04	9.56
4	0.15	0.20	–3.11	1.02	0.30	6.63
High Alpha	0.30	0.30	–11.14	0.99	0.55	–4.41
5-1 Diff.	1.39	0.72	–4.12	1.90	1.35	–8.08
t-stat.	(9.34)	(5.45)	(–9.58)	(7.68)	(6.06)	(–9.38)

Panel D. Liquid vs. Illiquid Stocks

	Liquid Stocks			Illiquid Stocks		
	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL
Low Alpha	–0.65	–0.26	1.15	–1.09	–0.94	–0.33
2	–0.10	–0.17	2.50	–0.27	–0.32	4.42
3	0.22	0.00	1.73	0.18	–0.07	3.53
4	0.54	0.22	0.65	0.35	0.41	0.26
High Alpha	0.99	0.25	–3.43	0.75	0.58	–9.83
5-1 Diff.	1.64	0.51	–4.58	1.84	1.52	–9.50
t-stat.	(7.78)	(4.34)	(–8.46)	(7.92)	(6.36)	(–11.77)

Panel E. High Volatility Uncertainty vs. Low Volatility Uncertainty

	Stocks with Low Volatility Uncertainty			Stocks with High Volatility Uncertainty		
	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL	ΔCVOL	ΔCVOL – ΔPVOL	ΔRVOL
Low Alpha	–1.05	–0.35	–2.31	–0.89	–0.89	1.29
2	–0.38	–0.14	0.69	–0.07	–0.40	6.46
3	–0.09	–0.03	0.22	0.62	0.04	5.49
4	0.27	0.14	–0.80	0.90	0.42	2.93
High Alpha	0.54	0.29	–6.85	0.98	0.62	–7.10
5-1 Diff.	1.60	0.64	–4.54	1.86	1.51	–8.39
t-stat.	(12.50)	(6.49)	(–9.46)	(7.06)	(6.12)	(–10.59)

Table 12. Predicting Systematic and Idiosyncratic Call Option Volatilities

This table presents the average slope coefficients from the firm-level cross-sectional regressions of systematic and idiosyncratic implied volatility changes on stock and option characteristics. The daily alphas are estimated based on the CAPM using daily return observations over the previous month. The monthly Alphas are calculated by summing the daily alphas in a month. The dependent variables are the next-month changes in total call implied volatilities, ΔCVOL, the next-month changes in systematic call implied volatilities, $\Delta CVOL^{sys}$, and the next-month changes in idiosyncratic call implied volatilities, $\Delta CVOL^{idio}$. $\Delta CVOL^{sys}$ and $\Delta CVOL^{idio}$ are defined in equation (7) using real measure betas. The control variables include market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), illiquidity (ILLIQ), realized-implied volatility spread (RVOL-IVOL), change in the call open interest (ΔOI^C), change in the put open interest (ΔOI^P), and the risk-neutral skewness (QSKEW). Newey-West t-statistics are given in parentheses. The sample period is from January 1996 to September 2008.

	ΔCVOL	$\Delta CVOL^{sys}$	$\Delta CVOL^{idio}$
ALPHA	2.1225	–0.5932	2.7309
	(3.88)	(–5.02)	(5.04)
BETA	–0.5192	–0.4741	–0.0471
	(–3.36)	(–2.23)	(–0.25)
SIZE	0.0651	0.0014	0.0630
	(1.60)	(0.05)	(1.37)
BM	–0.1551	–0.0188	–0.1379
	(–3.83)	(–0.96)	(–3.26)
MOM	0.0037	0.0032	0.0005
	(3.57)	(4.15)	(0.38)
ILLIQ	7.7977	–1.1593	8.9233
	(5.47)	(–3.25)	(6.06)
RVOL-IVOL	9.3746	0.3021	9.0270
	(10.26)	(6.30)	(9.65)
ΔOI^C	–1.0207	0.0245	–1.0410
	(–11.03)	(2.13)	(–10.89)
ΔOI^P	–0.5345	0.0065	–0.5368
	(–10.22)	(0.62)	(–10.43)
QSKEW	24.031	–0.0465	24.081
	(11.64)	(–0.29)	(11.67)

Table 13. Long-Term Predictability of Option Volatilities by Stock Alphas

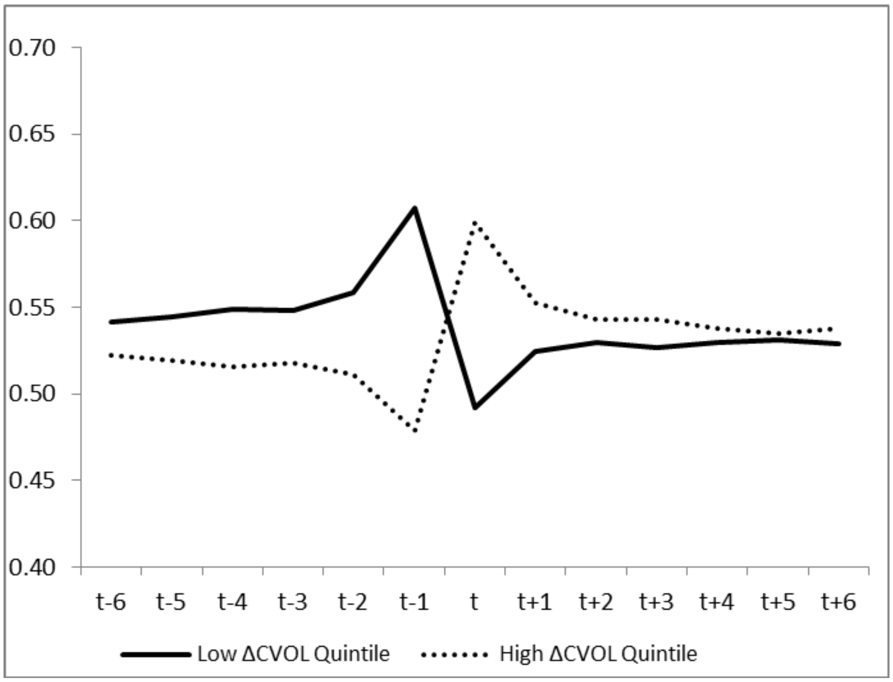
This table presents the long-term predictive power of the abnormal returns of individual stocks (CAPM Alphas) for forecasting future changes in call implied volatilities. The daily alphas are estimated based on the CAPM using daily return observations over the previous month. The monthly Alphas are calculated by summing the daily alphas in a month. Quintile portfolios are formed based on the monthly CAPM Alphas. We hold these portfolios for one to six months and rebalance monthly. Table reports the one- to six-month ahead 5-1 differences between average ΔCVOL values for Low Alpha and High Alpha portfolios. Newey-West t-statistics are given in parentheses. The sample period is from January 1996 to September 2008.

	1-month	2-month	3-month	4-month	5-month	6-month
5-1 Diff.	1.63	0.62	0.96	0.79	0.64	0.55
t-stat.	(7.75)	(4.01)	(6.28)	(6.18)	(5.83)	(5.10)

Figure 1. Implied Volatilities in the Pre- and Post-Formation Months

Panel A graphs the level of call implied volatilities for the Low ΔCVOL and High ΔCVOL quintiles from the dependent sorts of ΔCVOL and ΔPVOL portfolios formed at time *t* from month *t*–6 to month *t*+6. Panel B graphs the level of put implied volatilities for the Low ΔPVOL and High ΔPVOL quintiles from the dependent sorts of ΔCVOL and ΔPVOL portfolios formed at time *t* from month *t*–6 to month *t*+6.

Panel A



Panel B