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The Joint Cross Section of Stocks and Options

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ABSTRACT

Stocks with large increases in call (put) implied volatilities over the previous month tend to have high (low) future returns. Sorting stocks ranked into decile portfolios by past call implied volatilities produces spreads in average returns of approximately 1% per month, and the return differences persist up to six months. The cross section of stock returns also predicts option implied volatilities, with stocks with high past returns tending to have call and put option contracts that exhibit increases in implied volatility over the next month, but with decreasing realized volatility. These predictability patterns are consistent with rational models of informed trading.

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 simply functions of underlying stock prices and risk-free securities.[1] We show that the cross section of option volatilities contains information that forecasts the cross section of expected stock returns, and the cross section of stock-level characteristics forecasts option implied volatilities.

In the direction of option volatilities predicting stock returns, we find that stocks with call options that have experienced increases in implied volatilities over the past month tend to have high returns over the next month. Puts contain information independent from that in call options, especially puts whose implied volatilities move opposite from the direction predicted by put-call parity. After controlling for movements in call implied volatilities, increases in put option volatilities predict decreases in next-month stock returns. The strength

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[1] Many theoretical models jointly pricing options and underlying assets in incomplete markets have incorporated many of these real-world frictions. See Detemple and Selden (1991), Back (1993), Cao (1999), Buraschi and Jiltsov (2006), and Vanden (2008), among others.

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and persistence of this predictability for stock returns from the cross section of option volatilities is remarkable for several reasons.

First, the innovation in implied volatilities can be considered a very simple measure of news arrivals in the option market. While strongest for the next-month horizon, the predictability persists up to at least six months. The predictability at the standard monthly horizon suggests that it is unlikely due to microstructure trading effects. In contrast, most of the previous literature investigating lead-lag effects of option versus stock markets focuses on intraday or daily frequencies. These high-frequency studies largely find that both option and stock markets react quickly to news, and that, at daily frequencies or higher, options and stocks are fairly priced relative to each other.[2]

Second, the predictability is statistically very strong and economically large. Decile 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. Stocks sorted on past increases in their put implied volatilities after controlling for implied call volatilities exhibit spreads in average returns of greater than 1% per month between the extreme decile portfolios. 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 2008 to 2009 financial crisis, the ability of option volatilities to predict returns is still seen in recent data.

The predictability from options to stock returns is consistent with economies wherein informed traders choose the option market to trade first, such as those developed by Chowdhry and Nanda (1991) and Easley, O'Hara, and Srinivas (1998). This causes the option market to lead the stock market, where informed trading does not predominate. However, informed investors would not always choose just one market to trade. In a noisy rational expectations model of informed trading in both stock and option markets (detailed in Appendix A), we show that informed trading contemporaneously moves both option and stock markets. Informed traders who receive news about future firm cash flows can trade stocks, options, or both, and do so depending on the relative size of noise trading present in each market. Market makers, who are allowed to trade both stock and option markets, ensure that stock and option prices satisfy arbitrage bounds. The presence of noise traders in both stock and option markets allows informed traders to disguise their trades, so prices do not immediately adjust to fully revealing efficient levels, which would result in the absence of noise traders. The model implies that option volatilities can predict future stock returns. The model also indicates that the predictability should be highest

[2] At the daily or intraday frequencies, Manaster and Rendleman (1982), Bhattacharya (1987), and Anthony (1988) find that options predict future stock prices. Fleming, Ostdiek, and Whaley (1996) document that 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 that stock markets lead option markets. Chakravarty, Gulen, and Mayhew (2004) find that both stock and option markets contribute to price discovery, while Muravyev, Pearson, and Broussard (2013) find that price discovery occurs only in the stock market.

when the underlying volumes in both stock and option markets are largest, which we confirm in empirical tests.

Importantly, the model shows that informed trading also gives rise to stock-level information predicting option returns. Thus, both directions of predictability, from option markets to stock markets and vice versa, arise simultaneously. Consistent with the model, we also uncover evidence of reverse directional predictability from stock price variables to option markets. Many of the variables long known to predict stock returns also predict option implied volatilities.[3] 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 (put) implied volatilities increase over the next month by approximately 4% (2%).

The model also predicts that past stock returns predict future increases in option volatilities and future decreases in realized volatility of stock returns, which we confirm in the data. The intuition is that informed trading today causes prices to partially adjust, which resolves some of the future uncertainty in firm cash flows. Since some information is revealed in prices, future realized volatility of stock returns decreases. The predictability of option volatilities is stronger in stocks that exhibit a lower degree of predictability and stocks whose options are harder to hedge, consistent with other rational models. Behavioral overreaction theories predict that option implied volatilities should increase together with other measures of uncertainty such as earnings dispersion. We find this is not the case.

Our findings are related to a recent literature showing that option prices contain predictive information about stock returns. Cao, Chen, and Griffin (2005) find that merger information hits the call option market prior to the stock market, but focus only on these special corporate events. 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. Johnson and So (2012) show that the ratio of option market volume to equity market volume predicts stock returns. We control for all of these variables in examining the predictability of stock returns by lagged innovations in call and put option volatilities.

Our paper is related to Cremers and Weinbaum (2010), who examine the predictability of stock returns from violations of put-call parity. In passing, they examine the predictability of joint call and put volatility changes on stock returns, but do not examine their separate effects. They interpret their findings of stock return predictability by option information as informed investors preferring to trade in option markets first. Like Cremers and Weinbaum, our

[3] This predictability is inconsistent with standard arbitrage-free option pricing models, which a long literature has also shown. Earlier papers in this literature include Figlewski (1989) and Longstaff (1995). More recently, see Goyal and Saretto (2009), Cao and Han (2013), and Bali and Murray (2013).

results are consistent with informed trading, as we relate changes in option volatilities to contemporaneous changes in option volume. However, different from Cremers and Weinbaum, we show that the predictability of stock returns by past changes in option implied volatilities arises in a model of informed trading, which predicts that there should be predictability from the cross section of option to stock markets and vice versa.

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. 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. In contrast to these studies, 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). We also find that many of the "usual suspects" among commonly used stock characteristics that predict stock returns also predict the cross section of option implied volatilities, like book-to-market, momentum, and illiquidity measures.

The rest of the paper is organized as follows. Section I discusses the data and provides variable definitions. Sections II and III examine the predictive power of option implied volatility changes on the cross section of stock returns using stock portfolios and cross-sectional regressions, respectively. Section IV investigates the reverse direction of predictability from stock returns to realized and implied volatilities. Section V concludes.

I. Data

A. *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

Table I

Descriptive Statistics for Implied Volatilities

Panel A presents the average number of stocks per month for each year from 1996 to 2011. The average and standard deviation of the monthly call and put implied volatilities (*CVOL*, *PVOL*) are reported for each year from 1996 to 2011. 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 December 2011. Panel B reports the average firm-level cross-correlations of the levels and changes in implied volatilities, and the levels and changes in realized volatility.

Panel A: Summary Statistics for Call and Put Implied Volatilities

		CVOL		*PVOL*	
Date	# of Stocks	Average	Stdev	Average	Stdev
1996	1,261	42.55	20.60	43.35	20.54
1997	1,507	45.09	20.64	45.68	20.41
1998	1,689	51.21	22.23	51.53	21.51
1999	1,755	57.10	24.23	57.82	23.96
2000	1,624	71.57	31.89	72.71	31.79
2001	1,589	62.64	28.63	64.63	29.84
2002	1,654	55.22	24.48	56.56	26.25
2003	1,616	43.54	19.08	44.05	19.07
2004	1,729	39.08	18.13	39.86	18.76
2005	1,873	37.12	18.61	38.11	18.79
2006	1,974	37.29	17.45	38.09	17.83
2007	2,114	39.70	18.54	40.37	18.86
2008	2,104	60.24	24.48	62.73	26.12
2009	2,089	60.55	26.12	60.26	25.75
2010	2,175	46.56	22.83	45.96	23.49
2011	2,312	48.28	24.88	48.96	26.54
Average	1,816	49.86	22.68	50.67	23.10

Panel B: Average Firm-Level Correlations

	CVOL	*PVOL*	Δ*CVOL*	Δ*PVOL*	*RVOL*	Δ*RVOL*
CVOL	1					
PVOL	0.92	1				
Δ*CVOL*	0.27	0.15	1			
Δ*PVOL*	0.16	0.27	0.58	1		
RVOL	0.66	0.66	0.02	0.03	1	
Δ*RVOL*	0.02	0.03	0.08	0.10	0.47	1

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 December 2011. In the Internet Appendix, we also show that our results are similar using implied volatilities of actual options rather than the volatility surface.

Table I contains descriptive statistics for our sample. Panel A reports the average number of stocks per month for each year from 1996 to 2011. There are 1,261 stocks per month in 1996, rising to 2,312 stocks per month in 2011.

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 financial crisis in 2008 to 2009, we observe a significant increase in average implied volatilities from around 40% to 60% for both *CVOL* and *PVOL*.[4]

B. 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: [5]

BETA: Following Scholes and Williams (1977) and Dimson (1979), we take into account nonsynchronous trading by estimating an extended version of the market model at the daily frequency to obtain the monthly beta of an individual stock:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1} - r_{f,d-1}) + \beta_{2,i}(R_{m,d} - r_{f,d}) + \beta_{3,i}(R_{m,d+1} - r_{f,d+1}) + \varepsilon_{i,d}, \tag{1}$$

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 sum of the estimated slope coefficients, $\hat{\beta}_{1,i} + \hat{\beta}_{2,i} + \hat{\beta}_{3,i}$, is the market beta of stock i in month t. The adjustment of betas to nonsynchronous trading has little effect as we find very similar results using regular betas.

SIZE: Firm size is measured as 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.

[4] 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 nonsynchronous trades. These issues do not affect the use of our option volatilities as we use predictive instruments observable at the beginning of each period.

[5] Easley, Hvidkjaer, and O'Hara (2002) introduce a measure of the probability of information-based trading, *PIN*, and show empirically that stocks with higher *PIN* 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 either. See the Internet Appendix.

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 the 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 two months ago to avoid the short-term reversal effect, that is, momentum is the cumulative return from month $t{-}12$ to month $t{-}2$.

Illiquidity (ILLIQ): We use Amihud's (2002) definition of illiquidity. In particular, 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, $RVOL_{i,t} = \sqrt{\text{var}(R_{i,d})}$. We denote the monthly first differences in $RVOL$ as $\Delta RVOL$.

The next set of predictive variables pertains to option markets:

Implied Volatility Innovations: We define implied volatility innovations as the change in call and put implied volatilities, which we denote as $\Delta CVOL$ and $\Delta PVOL$, respectively:[6]

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

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 (implied volatilities exhibit significant time-series autocorrelation) and cross section (implied volatilities are predictable using cross-sectional stock characteristics). In the Internet Appendix, we consider two other measures accounting for these dimensions of predictability, and find that volatility innovations constructed from both time-series and cross-sectional models also predict stock returns.

[6] 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 ($\%\Delta CVOL$,$\%\Delta PVOL$) are available in the Internet Appendix.

Call/Put Volume (C/P VOLUME): The relation between option volume and underlying stock returns has been studied in the literature, with mixed findings by Stephan 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), among 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): Our second measure of option volume is the ratio of the open interest of call options to that of 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 a similar negative effect of the *RVOL-IVOL* spread on future option returns.

Risk-Neutral Skewness (QSKEW): Following Conrad, Dittmar, and Ghysels (2013) and Xing, Zhang, and Zhao (2010), we control for 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. In contrast, Conrad, Dittmar, and Ghysels (2013) report the opposite relation using a more general measure of risk-neutral skewness based on Bakshi, Kapadia, and Madan (2003), which is derived using the whole cross section of options.

C. Correlations of Volatility Innovations

Panel B of Table I 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, whereby, when current stock volatility increases, implied volatilities of all option contracts across all strikes and maturities also tend to rise. Note that, if put-call parity held exactly, then the correlation of *CVOL* and *PVOL* would be one. Put-call parity holds approximately (but not always, as Ofek, Richardson, and Whitelaw (2004) and Cremers and Weinbaum (2010) exploit), so, to examine the incremental predictive power of put volatilities, we control for the general volatility effect.[7] The persistence of the level of the volatility factor is also reflected in the high correlation (66%) of past realized volatility with both *CVOL* and *PVOL*.

[7] In the simplified model of Appendix A, put and call options are equivalent securities because we assume binomial payoffs.

The first differences in implied volatilities, $\Delta CVOL$ and $\Delta PVOL$, have a lower correlation of 58% than the correlation of 92% between the levels of *CVOL* and *PVOL*. The positive correlation between $\Delta CVOL$ and $\Delta PVOL$ reflects the common component in both call and put volatilities. The changes in implied volatilities are not correlated with either *RVOL* or $\Delta RVOL$, as correlations of $\Delta CVOL$ with *RVOL* and $\Delta RVOL$ are 0.02 and 0.08, respectively. The correlations of $\Delta PVOL$ with *RVOL* and $\Delta RVOL$ are also low at 0.03 and 0.10, 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.

II. Returns on Portfolios Sorted by Option Implied Volatilities

A. Univariate Portfolio Sorts

A.1. Portfolios Sorted by $\Delta CVOL$

Panel A of Table II shows that stocks that have past high changes in call implied volatilities have high future returns. We form decile portfolios ranked on $\Delta CVOL$ rebalanced every month. Portfolio 1 (Low $\Delta CVOL$) contains stocks with the lowest changes in call implied volatilities in the previous month and Portfolio 10 (High $\Delta CVOL$) includes stocks with the highest changes in call implied volatilities in the previous month. We equal weight stocks in each decile portfolio and rebalance monthly. Panel A of Table II shows that the average raw return of stocks in decile 1 with the lowest $\Delta CVOL$ is 0.29% per month and this monotonically increases to 1.38% per month for stocks in decile 10. The difference in average raw returns between deciles 1 and 10 is 1.09% per month, with a highly significant Newey-West *t*-statistic of 3.45. This result translates to a monthly Sharpe ratio of 0.26 and an annualized Sharpe ratio of 0.90 for an investment strategy taking a long position in High $\Delta CVOL$ stocks and a short position in Low $\Delta CVOL$ stocks.

The differences in returns between deciles 1 and 10 are very similar if we risk-adjust using the CAPM, at 1.04% per month, and the Fama-French (1993) model (FF3 hereafter) including market, size, and book-to-market factors, at 1.00% per month. In the final column, we conduct a characteristic match similar to Daniel and Titman (1997) and Daniel et al. (1997). The Daniel and Titman (1997) characteristic-matched procedure pairs each stock with a matching portfolio of firms that have approximately the same book-to-market and size. We use 100 portfolios, formed from the intersection of 10 portfolios sorted on size and 10 portfolios sorted on book-to-market following Daniel and Titman (1997). This procedure reduces the decile 1 and 10 difference to 0.86% per month (*t*-statistic of 2.87), but this difference is still both economically large and statistically significant.

Table II

Decile Portfolios of Stocks Sorted by $\Delta CVOL$ and $\Delta PVOL$

In Panel A, Portfolio 1 (Low $\Delta CVOL$) contains stocks with the lowest monthly changes in call implied volatilities in the previous month and Portfolio 10 (High $\Delta CVOL$) includes stocks with the highest monthly changes in call implied volatilities in the previous month. We equal-weight stocks in each decile portfolio and rebalance monthly. For each decile of $\Delta CVOL$, the columns report the average raw returns, the CAPM and three-factor Fama-French (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 10−1 Diff. reports the difference in average raw and risk-adjusted returns between the High $\Delta CVOL$ and Low $\Delta CVOL$ deciles. Newey-West t-statistics are given in parentheses. Panel B reports the corresponding results from the decile portfolios of $\Delta PVOL$. Panel C presents the corresponding results from the decile portfolios of $\Delta PVOL$-$\Delta CVOL$.

	Return	CAPM Alpha	FF3 Alpha	Characteristic-Control
Panel A: Decile Portfolios of Stocks Sorted by $\Delta CVOL$				
Low $\Delta CVOL$	0.29	−0.59	−0.74	−0.48
2	0.50	−0.27	−0.43	−0.31
3	0.65	−0.07	−0.23	−0.24
4	0.79	0.09	−0.05	−0.10
5	0.92	0.23	0.06	0.01
6	1.01	0.30	0.13	0.07
7	1.05	0.33	0.15	0.14
8	1.18	0.44	0.25	0.26
9	1.19	0.37	0.20	0.27
High $\Delta CVOL$	1.38	0.45	0.26	0.38
10−1 Diff.	1.09	1.04	1.00	0.86
t-stat.	(3.45)	(3.27)	(3.21)	(2.87)
Panel B: Decile Portfolios of Stocks Sorted by $\Delta PVOL$				
Low $\Delta PVOL$	0.94	0.06	−0.08	0.08
2	0.91	0.14	−0.01	0.03
3	0.88	0.14	−0.03	−0.04
4	0.84	0.13	−0.02	−0.08
5	0.89	0.20	0.02	−0.01
6	1.15	0.44	0.30	0.20
7	0.98	0.25	0.09	0.07
8	0.89	0.14	−0.05	0.01
9	0.98	0.17	−0.02	0.08
High $\Delta PVOL$	0.52	−0.40	−0.58	−0.34
10−1 Diff.	−0.42	−0.46	−0.50	−0.42
t-stat.	(−2.03)	(−2.14)	(−2.46)	(−2.61)
Panel C: Decile Portfolios of Stocks Sorted by $\Delta PVOL$-$\Delta CVOL$				
Low $\Delta PVOL$-$\Delta CVOL$	1.81	0.94	0.72	0.71
2	1.17	0.37	0.19	0.20
3	1.06	0.31	0.14	0.15
4	0.93	0.19	0.05	0.00
5	0.94	0.23	0.10	0.08
6	0.93	0.21	0.08	0.10

(Continued)

Table II—*Continued*

Panel C: Decile Portfolios of Stocks Sorted by $\Delta PVOL$-$\Delta CVOL$				
7	0.82	0.09	−0.05	−0.03
8	0.63	−0.13	−0.31	−0.21
9	0.58	−0.22	−0.38	−0.26
High $\Delta PVOL$-$\Delta CVOL$	0.13	−0.72	−0.93	−0.73
10−1 Diff.	−1.68	−1.66	−1.65	−1.44
t-stat.	(−6.77)	(−6.67)	(−6.49)	(−5.31)

A.2. Portfolios Sorted by $\Delta PVOL$

In Panel B of Table I, we form decile portfolios ranked on $\Delta PVOL$ rebalanced every month. Portfolio 1 (Low $\Delta PVOL$) contains stocks with the lowest changes in put implied volatilities in the previous month and Portfolio 10 (High $\Delta PVOL$) includes stocks with the highest changes in put implied volatilities in the previous month. Most of the returns to the $\Delta PVOL$ portfolios are approximately the same, with a notable difference for the stocks with the highest changes in past put implied volatilities, Portfolio 10. The average raw return difference between High $\Delta PVOL$ and Low $\Delta PVOL$ deciles is −0.42% per month, with a significant Newey-West t-statistic of −2.03. The CAPM and FF3 alpha differences between deciles 1 and 10 are, respectively, −0.46% and −0.50% per month, with t-statistics of −2.14 and −2.46. As shown in the last column of Panel B, the characteristic-matched portfolios of $\Delta PVOL$ also generate a negative and significant return difference of −0.42% per month with a t-statistic of −2.61.

The positive (negative) return spreads in the $\Delta CVOL$ ($\Delta PVOL$) portfolios are consistent with an informed trading story. If an informed "bullish" trader has good information that a stock is likely to go up next period, but the market does not completely react to the trades of the informed investor this period, then the informed investor can buy a call, which increases call option volatilities this period, and hence the stock price goes up the following period. A similar story holds for a "bearish" informed investor, betting that a stock will decrease in value, can buy a put, so increases in put implied volatilities forecast decreases in next-month stock returns.

Put and call options, however, are linked by put-call parity. Although put-call parity is only approximate—as the options are American, some stocks pay dividends, and violations of put-call parity do occur—increases in call implied volatilities are generally associated with increases in put implied volatilities. This causes a large common component in all option volatilities; indeed, in Table I, we see that $\Delta CVOL$ and $\Delta PVOL$ have a correlation of 0.58. Thus, although an informed trader receiving positive news could buy a call this period, which would generally increase call volatilities, or sell a put, which would generally decrease put volatilities, call and put volatilities tend not to move in opposite directions, especially outside arbitrage bounds.

The large common volatility component is perhaps responsible for some of the weaker predictability of $\Delta PVOL$ compared to the $\Delta CVOL$ portfolio sorts. To isolate the predictability of $\Delta PVOL$ compared to $\Delta CVOL$ (and vice versa), we should control for the overall implied volatility level. A rough way to look at the incremental predictive power of $\Delta PVOL$ controlling for the overall implied option level is to subtract the change in call implied volatilities, $\Delta CVOL$.

A.3. Portfolios Sorted by ΔPVOL-ΔCVOL

Panel C of Table II presents results from decile portfolios ranked on $\Delta PVOL$-$\Delta CVOL$ and rebalanced every month. Portfolio 1 (Low $\Delta PVOL$-$\Delta CVOL$) contains stocks with the lowest spread between $\Delta PVOL$ and $\Delta CVOL$ in the previous month and Portfolio 10 (High $\Delta PVOL$-$\Delta CVOL$) includes stocks with the highest spread between $\Delta PVOL$ and $\Delta CVOL$ in the previous month. Moving from deciles 1 to 10, average raw returns on the $\Delta PVOL$-$\Delta CVOL$ portfolios decrease from 1.81% to 0.13% per month. The difference in average raw returns between deciles 1 and 10 is −1.68% per month with a highly significant Newey-West t-statistic of −6.77. The differences in risk-adjusted returns between deciles 1 and 10 are very similar as well, with a CAPM alpha difference of −1.66% per month (t-statistic = −6.67) and a FF3 alpha difference of −1.65% per month (t-statistic = −6.49). As shown in the last column of Panel C, the characteristic-matched portfolios of $\Delta PVOL$-$\Delta CVOL$ also generate a negative and significant return difference, −1.44% per month with a t-statistic of −5.31, between the extreme deciles 1 and 10.

Simply taking the difference between $\Delta CVOL$ and $\Delta PVOL$ is a crude way of controlling for an overall volatility effect. We wish to test the predictability of $\Delta CVOL$ and $\Delta PVOL$ when jointly controlling for both effects. We expect to see stock returns increase most for those stocks in which bullish investors drive upward call option volatilities *and* simultaneously drive downward put option volatilities. We can jointly control for $\Delta CVOL$ and $\Delta PVOL$ effects in portfolios by constructing bivariate portfolio sorts, which we turn to now.

B. Bivariate Portfolio Sorts

B.1. Predictive Ability of ΔCVOL Controlling for ΔPVOL

To examine the predictive power of $\Delta CVOL$ controlling for $\Delta PVOL$, we need to create portfolios that exhibit differences in $\Delta CVOL$ with approximately the same levels of $\Delta PVOL$. We do this in Panel A of Table III.

We first perform a sequential sort by creating decile portfolios ranked by past $\Delta PVOL$.[8] Then, within each $\Delta PVOL$ decile, we form a second set of decile portfolios ranked on $\Delta CVOL$. This creates a set of portfolios with similar past

[8] It is possible to construct bivariate portfolios ranking on $\Delta CVOL$ and $\Delta PVOL$ based on independent sorts, which are reported in the Internet Appendix. Briefly, the return differences produced using independent sorts are larger than those reported in Table III. Controlling for $\Delta PVOL$, the average difference in returns (FF3 Alphas) between extreme $\Delta CVOL$ decile portfolios

Table III

Bivariate Portfolios of Stocks Sorted by $\Delta CVOL$ and $\Delta PVOL$

In Panel A, decile portfolios are first formed by sorting the optionable stocks based on $\Delta PVOL$. Then, within each $\Delta PVOL$ decile, stocks are sorted into decile portfolios ranked based on the monthly changes in call implied volatilities ($\Delta CVOL$) so that $\Delta CVOL1$ ($\Delta CVOL10$) contains stocks with the lowest (highest) $\Delta CVOL$. The column labeled $\Delta CVOL10$-$\Delta CVOL1$ shows the average raw return difference between High $\Delta CVOL$ ($\Delta CVOL10$) and Low $\Delta CVOL$ ($\Delta CVOL1$) portfolios within each $\Delta PVOL$ decile. The last column reports the corresponding Newey-West (1987) t-statistics in parentheses. Panel B performs a similar dependent sort procedure but first sequentially sorts on $\Delta CVOL$ and then on $\Delta PVOL$. The column labeled $\Delta PVOL10$-$\Delta PVOL1$ shows the average raw return difference between $\Delta PVOL10$ and $\Delta PVOL1$ portfolios within each $\Delta CVOL$ decile. In Panels A and B, Return Diff. reports the average raw return difference between $\Delta CVOL10$ ($\Delta PVOL10$) and $\Delta CVOL1$ ($\Delta PVOL1$) after controlling for $\Delta PVOL$ ($\Delta CVOL$). FF3 Alpha Diff. reports the 10−1 differences in the three-factor Fama-French (FF3) alphas. The monthly change in option trading volume and the monthly change in open interest are reported.

Panel A: Decile Portfolios of Stocks Sorted by $\Delta CVOL$ Controlling for $\Delta PVOL$

	$\Delta CVOL1$	$\Delta CVOL2$	$\Delta CVOL3$	$\Delta CVOL4$	$\Delta CVOL5$	$\Delta CVOL6$	$\Delta CVOL7$	$\Delta CVOL8$	$\Delta CVOL9$	$\Delta CVOL10$	$\Delta CVOL10$-$\Delta CVOL1$	t-stat.
$\Delta PVOL1$	0.23	0.85	0.12	0.93	0.92	0.74	1.21	1.68	1.03	1.76	1.54	(2.84)
$\Delta PVOL2$	0.62	0.21	0.83	0.45	0.84	0.69	1.08	0.89	1.44	2.09	1.47	(3.04)
$\Delta PVOL3$	0.28	0.69	0.57	0.78	0.86	0.51	0.86	1.35	1.07	1.80	1.52	(3.87)
$\Delta PVOL4$	0.60	0.18	0.38	1.12	0.65	0.78	0.85	0.71	1.29	1.96	1.36	(3.70)
$\Delta PVOL5$	0.11	0.46	0.60	0.89	0.93	1.08	1.00	1.07	1.05	1.75	1.63	(4.27)
$\Delta PVOL6$	0.79	1.28	0.71	0.96	1.22	1.25	1.17	1.05	1.48	1.58	0.79	(1.98)
$\Delta PVOL7$	0.10	0.59	0.50	1.04	1.12	1.11	1.19	1.17	1.22	1.81	1.71	(3.72)
$\Delta PVOL8$	0.53	0.49	1.07	0.89	0.66	0.74	1.03	0.85	1.30	1.29	0.76	(1.96)

(Continued)

Table III—*Continued*

Panel A: Decile Portfolios of Stocks Sorted by $\Delta CVOL$ Controlling for $\Delta PVOL$												
	$\Delta CVOL1$	$\Delta CVOL2$	$\Delta CVOL3$	$\Delta CVOL4$	$\Delta CVOL5$	$\Delta CVOL6$	$\Delta CVOL7$	$\Delta CVOL8$	$\Delta CVOL9$	$\Delta CVOL10$	$\Delta CVOL10$-$\Delta CVOL1$	t-stat.
$\Delta PVOL9$	0.21	0.39	0.39	1.10	1.02	1.09	1.12	1.00	1.71	1.81	1.60	(3.62)
$\Delta PVOL10$	−0.76	0.14	−0.18	0.72	1.21	0.94	0.97	0.48	1.22	0.62	1.38	(2.44)
$\Delta Volume^C$	7.9	−2.8	−27.0	−70.6	−63.0	−92.3	−72.6	−28.1	5.7	212.3		
ΔOI^C	38.5	30.9	22.2	22.4	24.1	23.8	48.8	66.4	107.5	218.6		
									Return Diff.		1.38	(5.85)
									FF3 Alpha Diff.		1.36	(5.22)

Panel B: Decile Portfolios of Stocks Sorted by $\Delta PVOL$ Controlling for $\Delta CVOL$												
	$\Delta PVOL1$	$\Delta PVOL2$	$\Delta PVOL3$	$\Delta PVOL4$	$\Delta PVOL5$	$\Delta PVOL6$	$\Delta PVOL7$	$\Delta PVOL8$	$\Delta PVOL9$	$\Delta PVOL10$	$\Delta PVOL10$-$\Delta PVOL1$	t-stat.
$\Delta CVOL1$	0.87	0.72	−0.11	0.58	1.04	0.20	0.33	−0.18	−0.11	−0.41	−1.28	(−3.61)
$\Delta CVOL2$	1.07	0.48	0.93	0.27	0.23	0.45	0.89	0.55	0.26	−0.10	−1.17	(−2.98)
$\Delta CVOL3$	1.44	0.80	0.70	0.88	0.27	0.58	0.31	0.50	0.62	0.34	−1.10	(−2.53)
$\Delta CVOL4$	0.81	1.08	0.74	0.67	1.05	0.71	0.84	0.97	0.49	0.54	−0.27	(−0.78)
$\Delta CVOL5$	1.91	1.08	0.80	0.85	1.03	0.86	0.91	0.88	0.79	0.10	−1.81	(−4.47)
$\Delta CVOL6$	0.99	0.73	0.94	0.80	1.21	1.24	0.82	1.51	0.92	0.92	−0.06	(−0.19)
$\Delta CVOL7$	1.41	0.95	1.25	1.45	0.90	1.13	1.06	1.09	0.70	0.60	−0.81	(−2.21)
$\Delta CVOL8$	1.73	1.87	1.32	1.31	0.76	0.85	0.94	1.27	1.31	0.49	−1.23	(−3.23)
$\Delta CVOL9$	1.57	1.30	1.44	0.91	1.43	1.45	1.13	1.01	1.07	0.60	−0.97	(−2.27)
$\Delta CVOL10$	2.13	2.24	1.65	1.53	1.56	1.42	1.37	1.24	0.19	0.44	−1.69	(−2.78)
$\Delta Volume^P$	−5.0	−18.3	−33.2	−48.7	−58.6	−49.1	−33.5	−3.1	48.5	153.8		
ΔOI^P	0.2	−2.3	2.0	5.3	4.6	18.0	28.0	44.5	64.5	112.2		
									Return Diff.		−1.04	(−6.40)
									FF3 Alpha Diff.		−1.06	(−6.38)

$\Delta PVOL$ characteristics with spreads in $\Delta CVOL$, and thus we can examine expected return differences due to $\Delta CVOL$ rankings controlling for the effect of $\Delta PVOL$. We hold these portfolios for one month and then rebalance at the end of the month. Table III, Panel A, reports the monthly percentage raw returns of these portfolios. As we move across the columns in Panel A, the returns generally increase from Low to High $\Delta CVOL$. The largest average portfolio returns are found near the top right-hand corner of Panel A, consistent with informed investors trading in option markets today to generate large positive $\Delta CVOL$ and large negative $\Delta PVOL$ changes, which predict stock price movements next period. Conversely, the most negative portfolio returns lie in the bottom left-hand corner where the largest $\Delta PVOL$ changes and the most negative $\Delta CVOL$ movements predict future decreases in stock prices.

In a given $\Delta PVOL$ decile portfolio, we can take the differences between the last and first $\Delta CVOL$ return deciles. We then average these return differentials across the $\Delta PVOL$ portfolios. This procedure creates a set of $\Delta CVOL$ portfolios with nearly identical levels of $\Delta PVOL$. Thus, we create portfolios ranking on $\Delta CVOL$ but controlling for $\Delta PVOL$. If the return differential is entirely explained by $\Delta PVOL$, no significant return differences will be observed across $\Delta CVOL$ deciles. These results are reported in the column labeled $\Delta CVOL10$-$\Delta CVOL1$. All of these return differences are around 1% per month or above, and they are highly statistically significant.

Panel A of Table III shows that the average raw return difference between the High $\Delta CVOL$ and Low $\Delta CVOL$ deciles is 1.38% per month, with a *t*-statistic of 5.85. The average three-factor Fama-French (FF3) alpha difference between the first and tenth $\Delta CVOL$ deciles averaged across the $\Delta PVOL$ portfolios is 1.36% per month, with a *t*-statistic of 5.22.[9]

B.2. Predictive Ability of ΔPVOL Controlling for ΔCVOL

Panel B of Table III repeats the same exercise as Panel A but performs a sequential sort first on $\Delta CVOL$ and then on $\Delta PVOL$. This produces portfolios with different $\Delta PVOL$ rankings after controlling for the information contained in $\Delta CVOL$, and allows us to examine the predictive ability of $\Delta PVOL$ controlling for $\Delta CVOL$. This set of sequential sorts produces slightly lower returns in absolute value than Panel A, reflecting the smaller spreads in the raw $\Delta PVOL$ sorts (see Table II), but they are still economically very large and highly statistically significant.

In Panel B, we observe the negative relation between increasing $\Delta PVOL$ and lower average returns in every $\Delta CVOL$ decile. Within each $\Delta CVOL$ decile, the average return differences between the High $\Delta PVOL$ and Low $\Delta PVOL$ portfolios ($\Delta PVOL10$-$\Delta PVOL1$) are in the range of -0.81% to -1.81% per month

is 1.81% (1.80%) per month. Controlling for $\Delta CVOL$, the average difference in returns (FF3 Alphas) between extreme $\Delta PVOL$ decile portfolios is -1.27% (-1.26%) per month.

[9] 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.

with Newey-West t-statistics ranging from -2.21 to -4.47, with only two exceptions in deciles 4 and 6, the average return differences between the High and Low $\Delta PVOL$ deciles are still negative but the t-statistics are statistically insignificant. The last two rows of Panel B average the differences between the first and tenth $\Delta PVOL$ deciles across the $\Delta CVOL$ deciles. This summarizes the returns to $\Delta PVOL$ after controlling for $\Delta CVOL$. The average return difference is -1.04% per month with a t-statistic of -6.40. The average difference in FF3 alphas is very similar at -1.06% per month with a t-statistic of -6.38. Thus, there is a strong negative relation between $\Delta PVOL$ and stock returns in the cross section after taking out the effect of the common volatility movements due to $\Delta CVOL$.

In both panels of Table III, we report the change in volume and open interest of calls and puts. Call volume and open interest tend to increase with the change in call implied volatilities. This is also true for put volume and open interest. This finding is consistent with the interpretation that the increase in implied volatilities may be due to informed investor demand. This increased demand, and the contemporaneous effect on option volatilities, may be due to the trading of options by certain investors with private information, which is borne out next period. Appendix A presents a model along these lines, and our results are consistent with this noisy rational expectations model of informed trading in both option and stock markets.

C. Characteristics of Δ*CVOL and* Δ*PVOL Portfolios*

To highlight the firm characteristics, risk, and skewness attributes of optionable stocks in the portfolios of $\Delta CVOL$ and $\Delta PVOL$, Table IV presents descriptive statistics for the stocks in the various deciles. The decile portfolios in Table IV are formed by sorting optionable stocks based on $\Delta CVOL$ controlling for $\Delta PVOL$ (Panel A) and $\Delta PVOL$ controlling for $\Delta CVOL$ (Panel B) formed as described in the previous section. In each month, we record the median values of various characteristics within each portfolio. These characteristics are all observable at the time the portfolios are formed. Table IV reports the average of the median characteristic values across months of market beta (*BETA*), log market capitalization (*SIZE*), book-to-market (*BM*), the cumulative return over the 11 months prior to portfolio formation (*MOM*), the return in the portfolio formation month (*REV*), the Amihud (2002) illiquidity ratio (*ILLIQ*), the realized skewness (*SKEW*), the coskewness (*COSKEW*), and the risk-neutral skewness (*QSKEW*).[10] The second columns in each panel report the next-month average return.

In Panel A of Table IV, as we move from the Low $\Delta CVOL$ to the High $\Delta CVOL$ decile, the average return on $\Delta CVOL$ portfolios increases from 0.27%

[10] *SKEW* and *COSKEW* are computed using daily returns over the past one year. Definitions of all other variables are given in Section II. As discussed in the Internet Appendix, the calculation of *COSKEW* follows Harvey and Siddique (2000), where we regress stock returns on the market and squared market returns. The slope coefficient on the squared market return is the *COSKEW* of Harvey and Siddique (2000).

Table IV

Descriptive Statistics for Decile Portfolios of Stocks Sorted by $\Delta CVOL$ and $\Delta PVOL$

In Panel A, decile portfolios are first formed by sorting the optionable stocks based on $\Delta PVOL$. Then, within each $\Delta PVOL$ decile, stocks are sorted into decile portfolios ranked based on the monthly changes in call implied volatilities ($\Delta CVOL$) so that $\Delta CVOL1$ ($\Delta CVOL10$) contains stocks with the lowest (highest) $\Delta CVOL$. Panel A presents average portfolio characteristics for each $\Delta CVOL$ decile averaged across the 10 $\Delta PVOL$ deciles to produce decile portfolios with dispersion in $\Delta CVOL$, but that contain all $\Delta PVOL$ values. This procedure creates a set of $\Delta CVOL$ portfolios with similar levels of $\Delta PVOL$, and thus these $\Delta CVOL$ portfolios control for differences in $\Delta PVOL$. For each $\Delta CVOL$ decile (controlling for $\Delta PVOL$), Panel A reports the average across months in the sample of the median values within each month of various characteristics for the optionable stocks—one-month-ahead return (Return), three-factor Fama-French alpha (FF3 alpha), market beta (*BETA*), log market capitalization (*SIZE*), book-to-market (*BM*), the cumulative return over the 11 months prior to portfolio formation (*MOM*), the return in the portfolio formation month (*REV*), illiquidity (*ILLIQ*), realized skewness (*SKEW*), coskewness (*COSKEW*), and risk-neutral skewness (*QSKEW*). *SKEW* and *COSKEW* are computed using daily returns over the past one year. *QSKEW* is defined as the difference between out-of-the-money put implied volatility and the average of at-the-money call and put implied volatilities. Panel B reports the corresponding results for the decile portfolios of $\Delta PVOL$ controlling for $\Delta CVOL$.

	Return	FF3 alpha	*BETA*	*SIZE*	*BM*	*MOM*	*REV*	*ILLIQ*	*SKEW*	*COSKEW*	*QSKEW*
Panel A: Decile Portfolios of Stocks Sorted by $\Delta CVOL$ Controlling for $\Delta PVOL$											
Low $\Delta CVOL$	0.27	−0.53	1.17	6.45	0.50	−1.18	3.87	0.110	0.29	−1.55	6.28
2	0.53	−0.17	1.12	7.10	0.49	5.32	2.48	0.055	0.24	−0.94	5.36
3	0.50	−0.17	1.11	7.45	0.48	8.77	1.83	0.037	0.22	−0.63	4.86
4	0.89	0.24	1.08	7.64	0.47	10.59	1.24	0.030	0.21	−0.55	4.60
5	0.94	0.33	1.07	7.72	0.47	12.01	0.80	0.028	0.21	−0.54	4.38

(Continued)

Table IV—*Continued*

	Return	FF3 alpha	*BETA*	*SIZE*	*BM*	*MOM*	*REV*	*ILLIQ*	*SKEW*	*COSKEW*	*QSKEW*
Panel A: Decile Portfolios of Stocks Sorted by $\Delta CVOL$ Controlling for $\Delta PVOL$											
6	0.89	0.26	1.08	7.73	0.47	12.18	0.39	0.027	0.21	−0.45	4.24
7	1.05	0.40	1.11	7.63	0.48	11.57	−0.20	0.032	0.22	−0.34	4.13
8	1.03	0.34	1.12	7.44	0.48	10.84	−0.98	0.041	0.21	−0.62	4.03
9	1.28	0.53	1.17	7.10	0.49	9.33	−1.91	0.060	0.23	−1.07	3.67
High $\Delta CVOL$	1.65	0.83	1.23	6.45	0.50	3.51	−4.06	0.126	0.25	−1.73	2.25
Panel B: Decile Portfolios of Stocks Sorted by $\Delta PVOL$ Controlling for $\Delta CVOL$											
Low $\Delta PVOL$	1.39	0.60	1.29	6.48	0.47	−0.89	5.67	0.10	0.31	−1.50	6.28
2	1.13	0.41	1.15	7.04	0.48	4.69	3.90	0.06	0.25	−0.86	5.35
3	0.97	0.31	1.07	7.40	0.49	8.04	2.89	0.04	0.22	−0.64	4.93
4	0.93	0.29	1.02	7.62	0.49	9.07	1.93	0.03	0.21	−0.67	4.54
5	0.95	0.32	1.00	7.71	0.49	9.93	1.10	0.03	0.20	−0.48	4.37
6	0.89	0.25	1.01	7.72	0.49	10.70	0.30	0.03	0.20	−0.55	4.23
7	0.86	0.19	1.04	7.63	0.49	11.28	−0.59	0.03	0.21	−0.64	4.03
8	0.88	0.18	1.11	7.46	0.48	11.97	−1.71	0.04	0.21	−0.66	3.94
9	0.62	−0.10	1.18	7.15	0.49	10.89	−3.32	0.06	0.23	−0.67	3.63
High $\Delta PVOL$	0.35	−0.45	1.38	6.50	0.47	6.91	−6.52	0.12	0.25	−1.59	2.62

to 1.65%. The return spread between the extreme decile portfolios is 1.38% per month, with a t-statistic of 5.85. Controlling for $\Delta PVOL$ has produced a larger spread between the deciles 10 and 1 returns of 1.09% in Table II, consistent with $\Delta CVOL$ and $\Delta PVOL$ representing different effects. In Panel A of Table IV, the difference in FF3 alphas between decile portfolios 1 and 10 is 1.36% per month, with a t-statistic of 5.22. Consistent with there being little difference in the raw return spread versus the FF3 alpha spread, there are no discernible patterns of market beta, size, and book-to-market across the portfolios. Illiquidity also cannot be an explanation, as the *ILLIQ* loadings are U-shaped across the $\Delta CVOL$ deciles. In fact, stocks with the most negative and largest changes in $\Delta CVOL$ tend to be the most liquid stocks.

There is, however, a strong reversal effect, with stocks in the Low $\Delta CVOL$ decile having the highest past one-month return of 3.87% and stocks in the High $\Delta CVOL$ decile having the lowest past one-month return of −4.06%. In the Internet Appendix, we construct a five-factor model that augments the Fama-French (1993) model with a momentum factor (see Carhart (1997)) and a short-term reversal factor. The difference in average returns between the Low $\Delta CVOL$ and High $\Delta CVOL$ deciles controlling for the five factors is 1.37% per month, with a t-statistic of 5.24. Thus, the return differences to $\Delta CVOL$ are not due to short-term reversals.

We investigate whether the skewness attributes of optionable stocks provide an explanation for the high returns of stocks with large past changes in $\Delta CVOL$ in the last three columns of Table IV. Panel A shows that there are no increasing or decreasing patterns across the $\Delta CVOL$ deciles for realized skewness (*SKEW*) or systematic skewness (*COSKEW*). In contrast, there is a pronounced pattern of decreasing risk-neutral skewness (*QSKEW*) moving from 6.28 for the first $\Delta CVOL$ decile to 2.25 for the tenth $\Delta CVOL$ decile. Recall that *QSKEW* is computed as the spread between the implied volatilities of out-of-the-money puts and at-the-money calls. Thus, decreasing *QSKEW* across the $\Delta CVOL$ deciles is equivalent to these stocks experiencing simultaneous declines in past put volatilities as $\Delta CVOL$ increases. This is consistent with informed trading whereby informed bullish investors with a high degree of confidence in future price appreciation buy calls and sell puts. Below, in cross-sectional regressions, we control for *QSKEW* along with other regressors in examining $\Delta CVOL$ and $\Delta PVOL$ predictability.

In Panel B of Table IV, we report similar descriptive statistics for the portfolios sorted on $\Delta PVOL$ after controlling for $\Delta CVOL$. Like the $\Delta CVOL$ portfolios in Panel A, we observe no obvious patterns in *BETA*, *SIZE*, *BM*, or *ILLIQ* that can explain the returns of the $\Delta PVOL$ portfolios, which decrease from 1.39% for stocks with the lowest past $\Delta PVOL$ to 0.35% for stocks with the highest past $\Delta PVOL$. The spread between deciles 1 and 10 is −1.04% per month, with a highly significant t-statistic of −6.40. The difference in FF3 alphas between the extreme deciles is −1.06% per month, with a t-statistic of −6.38.

Like Panel A, there is a strong pattern of decreasing past one-month returns (*REV*) as we move across the $\Delta PVOL$ deciles. The return in the portfolio formation month (*REV*), however, goes in the same direction as the next-month returns, decreasing from 5.67% for the first $\Delta PVOL$ decile (with a next-month return of 1.39%) to −6.52% for the tenth $\Delta PVOL$ decile (with a next-month return of 0.35%). Therefore, *REV* cannot simultaneously explain the opposite patterns of the high returns to past $\Delta CVOL$ stocks and the low returns to past $\Delta PVOL$ stocks. When we compute alphas with respect to the five-factor model that includes a short-term reversal factor, we find the difference in alphas between the first and tenth $\Delta PVOL$ portfolios is −1.05% per month, with a t-statistic of −6.56.

In the Internet Appendix, we further examine the predictability of implied volatility innovations in different size, liquidity, and price buckets. We find that the predictability is strongest in the smallest stocks, but the predictability of both $\Delta CVOL$ and $\Delta PVOL$ is still economically large and highly statistically significant among big stocks. The degree of $\Delta CVOL$ and $\Delta PVOL$ predictability is also similar among relatively liquid versus relatively illiquid stocks, and low-priced stocks versus high-priced stocks. The reduction, but not elimination, of the anomalous returns in the larger and more liquid stocks indicates that there may be some liquidity frictions involved in implementing a tradable strategy based on $\Delta CVOL$ and $\Delta PVOL$ predictors. In the Internet Appendix, we present further results for other screens related to liquidity and transactions costs, such as excluding the smallest, least liquid, and lowest priced stocks in the formation of our portfolios. In all these cases, there remain economically and statistically significant next-month returns from forming portfolios ranked on $\Delta CVOL$ and $\Delta PVOL$.

D. Long-Term Predictability

We investigate the longer-term predictive power of $\Delta CVOL$ and $\Delta PVOL$ over the next six months by constructing portfolios with overlapping holding periods following Jegadeesh and Titman (1993). In a given month t, the strategy holds 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 $\Delta CVOL$ controlling for $\Delta PVOL$ over the past month. Based on these rankings, 10 portfolios are formed for $\Delta CVOL$. In each month t, the strategy buys stocks in the High $\Delta CVOL$ decile and sells stocks in the Low $\Delta CVOL$ decile, 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. Decile portfolios of $\Delta PVOL$ 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 V. The average raw and risk-adjusted return differences between High $\Delta CVOL$ and Low $\Delta CVOL$ portfolios are statistically significant for one- to six-month holding periods. There is a pronounced drop in the magnitude of the average holding return,

Table V

Long-Term Predictability

This table presents the bivariate portfolios of Δ*CVOL* and Δ*PVOL* based on the dependent sorts. We hold these portfolios for one to six months and rebalance them monthly. In the first panel, decile portfolios are first formed by sorting the optionable stocks based on Δ*PVOL*. Then, within each Δ*PVOL* decile, stocks are sorted into decile portfolios ranked based on the monthly changes in call implied volatilities (Δ*CVOL*) so that Δ*CVOL1* (Δ*CVOL10*) contains stocks with the lowest (highest) Δ*CVOL*. The second panel performs a similar dependent sort procedure but first sequentially sorts on Δ*CVOL* and then on Δ*PVOL*. The first panel reports the one-month- to six-month-ahead average raw and risk-adjusted return differences between High Δ*CVOL* and Low Δ*CVOL* portfolios after controlling for Δ*PVOL*. The second panel reports the one-month- to six-month-ahead average raw and risk-adjusted return differences between High Δ*PVOL* and Low Δ*PVOL* portfolios after controlling for Δ*CVOL*. Newey-West (1987) *t*-statistics are reported in parentheses.

	1-Month	2-Month	3-Month	4-Month	5-Month	6-Month
Ranking on Δ*CVOL* Controlling for Δ*PVOL*						
Average Return Diff.	1.38	0.63	0.47	0.34	0.29	0.25
	(5.85)	(5.20)	(4.32)	(4.39)	(4.17)	(3.38)
FF3 Alpha Diff.	1.36	0.59	0.44	0.32	0.27	0.23
	(5.22)	(4.60)	(3.72)	(3.50)	(3.37)	(2.88)
Ranking on Δ*PVOL* Controlling for Δ*CVOL*						
Average Return Diff.	−1.04	−0.47	−0.27	−0.16	−0.11	−0.07
	(−6.40)	(−6.60)	(−3.82)	(−2.64)	(−2.12)	(−1.54)
FF3 Alpha Diff.	−1.06	−0.48	−0.27	−0.15	−0.10	−0.07
	(−6.38)	(−6.47)	(−3.50)	(−2.31)	(−1.88)	(−1.55)

which is reduced by more than one-half between months 1 and 2 from 1.38% per month to 0.63% per month, respectively. There is a further reduction to 0.34% per month after four months. We observe similar reductions in the alphas across horizons. Clearly, the predictability of Δ*CVOL* is not just a one-month affair, but it is concentrated within the next three months. The predictability of Δ*PVOL* also persists beyond one month. The average return difference between the extreme Δ*PVOL* decile portfolios controlling for Δ*CVOL* is −1.04% per month at the one-month horizon, and, like the long-horizon return predictability pattern for the Δ*CVOL* portfolios, the predictability decreases by approximately one-half to −0.47% per month at the two-month horizon. After three months, the economic and statistical significance of Δ*PVOL* portfolios disappears.

In summary, Δ*CVOL* and Δ*PVOL* predictability persists for at least three months, even longer in the case of Δ*CVOL*, but the strength of the predictability is reduced by half after one month in both cases.

E. Response of Option Markets

The portfolio-level analyses in Tables II to V show that the stock market reacts to option market information. As Table III shows, the large changes in option prices occur contemporaneously with option volume. Is all this information impounded in option prices today?[11]

We investigate this question by looking at the pattern of implied volatilities in the pre- and postformation months. Taking the dependent 10×10 sorts constructed in Table III, 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 $\Delta CVOL$ and High $\Delta CVOL$ deciles from the dependent sorts of $\Delta CVOL$ controlling for $\Delta PVOL$ portfolios formed at time t from month $t-6$ to month $t+6$. For the Low $\Delta CVOL$ decile, call implied volatilities decrease from 66% to 56% from month $t-2$ to month t, but then they increase to 58% in month $t+1$ and remain at about the same level over the next six months. Similarly, for the High $\Delta CVOL$ decile, call implied volatilities first increase from 55% to 66% from month $t-2$ to month t, but then they decrease to 59% in month $t+1$ and remain around there over the next six months. Thus, after call option volatilities increase prior to time t, stock prices respond after time t, but there is little response of option markets after the initial increase in $\Delta CVOL$.

Panel B of Figure 1 repeats the same exercise for the Low $\Delta PVOL$ and High $\Delta PVOL$ deciles, and also shows that there is no movement in put implied volatilities in the postformation months. This is also consistent with the interpretation that informed traders move option prices today and that there is little further adjustment, on average, in option markets, whereas equity returns adjust over the next few months. While Figure 1 examines only the pre- and postformation movements in option markets, below, we show that, consistent with the model in the Appendix, informed traders contemporaneously move both stock and option markets in the preformation period. Today's information in option volatilities, however, predicts stock returns for several months afterwards.

III. Cross-Sectional Regressions with $\Delta CVOL$ and $\Delta PVOL$

While the analysis in Table IV shows that most firm characteristics and skewness measures are unlikely to play a role in the predictability of the cross section of stock returns by $\Delta CVOL$ and $\Delta PVOL$, it does not control simultaneously for multiple sources of risk. We now do so using Fama and MacBeth (1973) regressions of stock returns onto implied volatility changes with other variables. Specifically, we run the following cross-sectional regression:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \Delta CVOL_{i,t} + \lambda_{2,t} \cdot \Delta PVOL_{i,t} + \lambda_{3,t} \cdot X_{i,t} + \varepsilon_{i,t+1}, \qquad (3)$$

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 control variables observable at time t for stock i, which includes information from the cross section of stocks and the cross section of options. We estimate the regression in equation (3) across stocks i at time t and then report the cross-sectional coefficients averaged across the sample. The

[11] We thank a referee for suggesting this analysis.

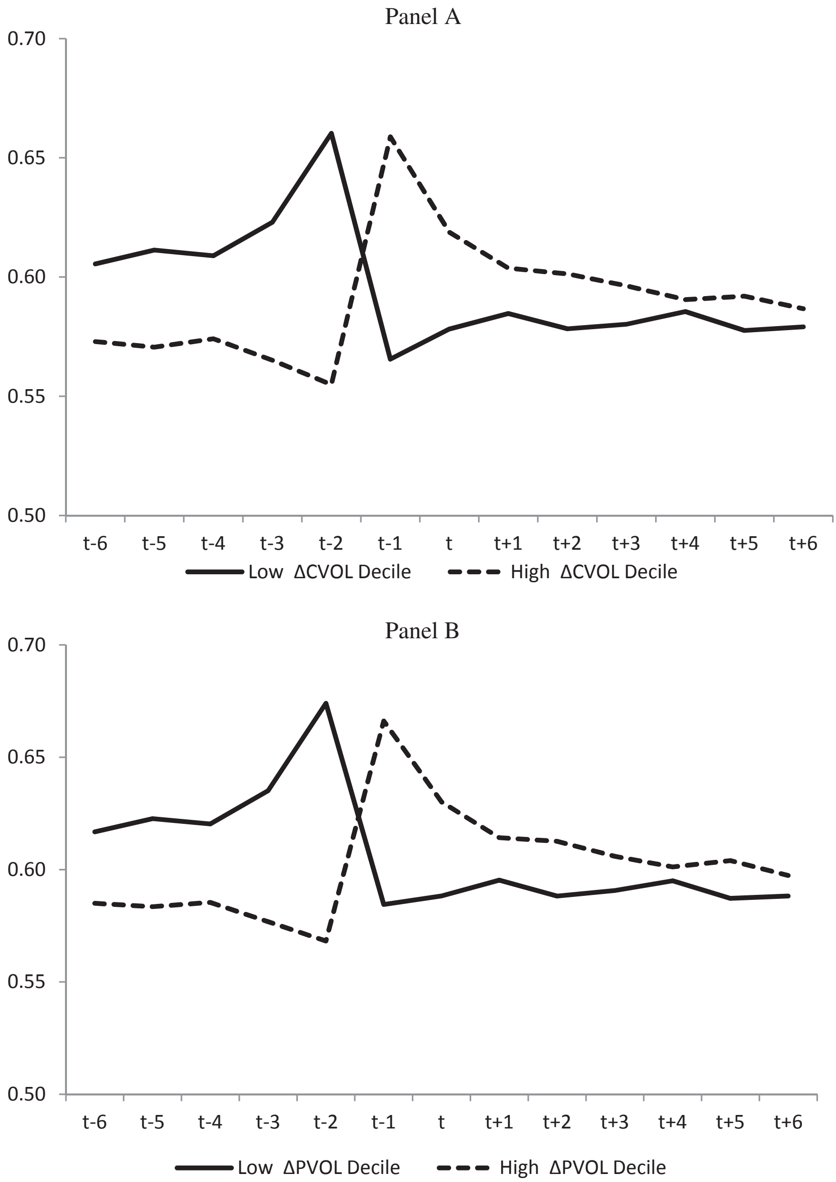

Figure 1. Implied volatilities in the pre- and post-formation months. Panel A graphs the level of call implied volatilities for the Low $\Delta CVOL$ and High $\Delta CVOL$ deciles from the dependent sorts of $\Delta CVOL$ and $\Delta PVOL$ portfolios formed at time t from month $t-6$ to month $t+6$. Panel B of Figure 1 graphs the level of put implied volatilities for the Low $\Delta PVOL$ and High $\Delta PVOL$ deciles from the dependent sorts of $\Delta CVOL$ and $\Delta PVOL$ portfolios formed at time t from month $t-6$ to month $t+6$.

cross-sectional regressions are run at the monthly frequency from March 1996 to December 2011. To compute standard errors, we take into account potential autocorrelation and heteroscedasticity in the cross-sectional coefficients, and we compute Newey-West (1987) t-statistics on the time series of slope coefficients. The Newey-West standard errors are computed with six lags.

A. Coefficients on $\Delta CVOL$ and $\Delta PVOL$

Table VI, Panel A, presents firm-level cross-sectional regressions with call and put implied volatility innovations first introduced individually and then simultaneously, together with controls for firm characteristics and risk factors.[12] We also include $\Delta CVOL$ and $\Delta PVOL$ simultaneously in multivariate regressions with control variables to determine their joint effects on stock returns. In the presence of risk loadings and firm characteristics, regression (1) in Panel A of Table VI shows that the average slope coefficient on $\Delta CVOL$ is 1.57, which is highly significant with a t-statistic of 3.13. In regression (2), the average slope coefficient on $\Delta PVOL$ is -1.85 with a t-statistic of -3.78. In regression (3), which includes both $\Delta CVOL$ and $\Delta PVOL$, the average slope coefficients are 3.78 and -3.92, with t-statistics of 7.09 and -7.13, respectively. These regressions confirm the robustness of $\Delta CVOL$ and $\Delta PVOL$ predicting future stock returns, as reported in Tables II to V, except the regressions control for a comprehensive set of firm characteristics, risk, and skewness attributes.

To provide a sense of the economic significance of the average slope coefficients in Table VI on $\Delta CVOL$ and $\Delta PVOL$, we construct the empirical cross-sectional distribution of implied volatility innovations over the full sample (summarized in Table I). The difference in $\Delta CVOL$ ($\Delta PVOL$) values between average stocks in the first and tenth deciles is 22.4% (19.4%) for call (put) implied volatility innovations. If a firm were to move from the first decile to the tenth decile of implied volatilities while its other characteristics were held constant, what would be the change in that firm's expected return? The $\Delta CVOL$ coefficient of 3.78 in Table VI, Panel A, represents an economically significant effect of an increase of $3.78 \times 22.42\% = 0.85\%$ per month in the average firm's expected return for a firm moving from the first to the tenth decile of implied volatilities, and the $\Delta PVOL$ coefficient of -3.92 represents a similar decrease of $-3.92 \times 19.41\% = -0.76\%$ per month. These figures are smaller than, but similar to, the 1.38% and -1.04% differences in the first and tenth deciles in Table IV for $\Delta CVOL$ and $\Delta PVOL$, respectively, because we control for the effects of all other firm characteristics, risk factors, and loadings.

[12] To address potential concerns about outliers, we eliminate the 1st and 99th percentiles of $\Delta CVOL$ and $\Delta PVOL$ and replicate Table VI. As a further robustness check, in addition to excluding the 1st and 99th percentiles of $\Delta CVOL$ and $\Delta PVOL$, we eliminate low-priced stocks (price < \$5 per share). As shown in the Internet Appendix, the average slope coefficients on $\Delta CVOL$ ($\Delta PVOL$) remain positive (negative) and highly significant after eliminating the low-priced stocks as well as the extreme observations for call and put implied volatilities.

Table VI

Fama-MacBeth Cross-Sectional Regressions with Implied Volatility Innovations

Panel A presents the firm-level cross-sectional regressions of equity returns on the monthly changes in call and put implied volatilities ($\Delta CVOL$, $\Delta PVOL$) after controlling for market beta (*BETA*), log market capitalization (*SIZE*), log book-to-market (*BM*), momentum (*MOM*), illiquidity (*ILLIQ*), short-term reversal (*REV*), realized stock return volatility (*RVOL*), log ratio of call-put option trading volume (*C/P VOLUME*), log ratio of call-put open interest (*C/P OI*), realized-implied volatility spread (*RVOL-IVOL*), and risk-neutral skewness (*QSKEW*). *PastRetDecile* is a variable that takes values from 1 to 10 for stocks in decile portfolios ranked on past one-month return. Panel B reports the firm-level Fama-MacBeth (1973) cross-sectional regressions in equation (4). The one-month-ahead returns of individual stocks are regressed on the asymmetric call and put implied volatility shocks; $\Delta CVOL^{HighCallVol}$, $\Delta CVOL^{LowCallVol}$, $\Delta PVOL^{HighPutVol}$, and $\Delta PVOL^{LowCallVol}$ are defined below equation (4). The results are presented for at-the-money 30-day options. The average slope coefficients and their Newey-West (1987) t-statistics are reported in parentheses. The last row reports the average R^2 values and their Newey-West (1987) t-statistics in parentheses.

Panel A: Predicting Equity Returns by $\Delta CVOL$, $\Delta PVOL$, and Other Predictors								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta CVOL$	1.5729		3.7754	3.8148	0.2208		2.4701	3.6963
	(3.13)		(7.09)	(7.09)	(0.29)		(3.15)	(6.96)
$\Delta PVOL$		−1.8513	−3.9228	−4.0506		−3.0181	−3.7990	−5.1524
		(−3.78)	(−7.13)	(−7.70)		(−4.33)	(−6.98)	(−6.71)
$\Delta CVOL\times$ *PastRetDecile*					0.3086		0.2822	
					(2.63)		(2.37)	
$\Delta PVOL\times$ *PastRetDecile*						0.3075		0.3321
						(2.23)		(2.37)
BETA	−0.0018	−0.0051	−0.0060	0.0086	−0.0953	−0.1029	−0.1033	−0.1004
	(−0.03)	(−0.09)	(−0.10)	(0.10)	(−0.61)	(−0.65)	(−0.66)	(−0.64)
SIZE	−0.1085	−0.0956	−0.1038	−0.0614	−0.1017	−0.0895	−0.0967	−0.0968
	(−1.42)	(−1.26)	(−1.36)	(−0.65)	(−1.36)	(−1.21)	(−1.30)	(−1.30)
BM	0.3066	0.3100	0.3056	0.3472	0.3034	0.3078	0.3020	0.3032
	(2.67)	(2.69)	(2.69)	(2.48)	(2.71)	(2.74)	(2.72)	(2.73)
MOM	−0.0006	−0.0006	−0.0007	−0.0012	−0.0010	−0.0009	−0.0010	−0.0010
	(−0.17)	(−0.15)	(−0.18)	(−0.31)	(−0.24)	(−0.23)	(−0.25)	(−0.26)
ILLIQ	0.1520	0.1595	0.1496	0.1326	0.1561	0.1600	0.1550	0.1509
	(1.33)	(1.40)	(1.33)	(1.21)	(1.44)	(1.47)	(1.44)	(1.40)
REV	−0.0192	−0.0236	−0.0203	−0.0182	−0.0193	−0.0232	−0.0203	−0.0201
	(−2.40)	(−2.82)	(−2.50)	(−2.16)	(−2.43)	(−2.82)	(−2.52)	(−2.51)

(Continued)

Table VI—*Continued*

Panel A: Predicting Equity Returns by $\Delta CVOL$, $\Delta PVOL$, and Other Predictors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RVOL	−0.8069	−0.6731	−0.7221		−0.6201	−0.5033	−0.5388	−0.5536
	(−1.31)	(−1.09)	(−1.17)		(−1.08)	(−0.89)	(−0.95)	(−0.98)
C/P VOLUME	−0.0005	−0.0017	−0.0022	0.0051	−0.0043	−0.0059	−0.0059	−0.0058
	(−0.01)	(−0.04)	(−0.05)	(0.12)	(−0.10)	(−0.14)	(−0.14)	(−0.14)
C/P OI	0.0653	0.0631	0.0641	0.0639	0.0659	0.0651	0.0642	0.0659
	(1.19)	(1.14)	(1.17)	(1.15)	(1.19)	(1.18)	(1.17)	(1.20)
RVOL-IVOL				−0.6880				
				(−2.39)				
QSKEW	−2.7798	−3.1336	−2.2963	−2.1563	−2.5636	(−2.9302	−2.0866	−2.1124
	(−4.61)	(−5.32)	(−4.08)	(−3.71)	(−4.37)	(−5.10)	(−3.80)	(−3.80)
R^2	9.00%	9.00%	9.15%	8.32%	9.31%	9.31%	9.45%	9.46%
	(10.93)	(10.95)	(11.09)	(11.63)	(10.92)	(10.93)	(11.07)	(11.07)

Panel B: Predicting Equity Returns by Asymmetric Volatility Shocks

	(1)	(2)	(3)	(4)
$\Delta CVOL_{i,t}^{HighCallVol}$	2.8653		4.2746	3.7228
	(3.18)		(4.45)	(4.74)
$\Delta CVOL_{i,t}^{LowCallVol}$	1.2417		3.4141	2.5113
	(1.72)		(4.42)	(3.60)
$\Delta PVOL_{i,t}^{HighPutVol}$		−1.5763	−3.7445	−3.3785
		(−3.06)	(−5.97)	(−5.47)
$\Delta PVOL_{i,t}^{LowPutVol}$		−0.3728	−1.8225	−1.2716
		(−0.49)	(−2.52)	(−1.95)
Coefficient Tests				
$\Delta CVOL_{i,t}^{HighCallVol} = \Delta CVOL_{i,t}^{LowCallVol}$	$t = 2.14$			
$\Delta PVOL_{i,t}^{HighPutVol} = PCVOL_{i,t}^{LowPutVol}$		$t = 2.33$		
Joint Test				
$\Delta CVOL_{i,t}^{HighCallVol} = \Delta CVOL_{i,t}^{LowCallVol}$,				
$\Delta PVOL_{i,t}^{HighPutVol} = PCVOL_{i,t}^{LowPutVol}$			Wald = 7.16 ($p = 2.78\%$)	Wald = 11.04 ($p = 0.40\%$)
Other Controls	No	No	No	Yes

B. Other Cross-Sectional Predictors

In Panel A of Table VI, the signs of the estimated Fama-MacBeth slope coefficients on the stock characteristics are consistent with earlier studies, but some of the relations are generally not significant. The log market capitalization (*SIZE*) and illiquidity (*ILLIQ*) coefficients are both insignificantly different from zero. The momentum (*MOM*) effect is weak as well. This is because we use optionable stocks that are generally large and liquid, where the size and liquidity effects are weaker (see, for example, Hong, Lim, and Stein (2000)). We do observe a significant book-to-market effect (see Fama and French (1992, 1973)) and a significant reversal effect (see Jegadeesh (1990) and Lehmann (1990)).

The most interesting predictors for our purposes, however, are the ones related to volatility and the option market. In regressions (1) to (3), the coefficient on historical volatility, *RVOL*, is negative but statistically insignificant.[13] Panel B of Table I reports that *RVOL* has very low correlations of 0.02 and 0.03 with Δ*CVOL* and Δ*PVOL*, respectively. This indicates that the effect of past volatility is very different from our cross-sectional predictability of Δ*CVOL* and Δ*PVOL*. 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 highly correlated. The Δ*CVOL* and Δ*PVOL* coefficients are similar across regressions (3) and (4).

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. However, our results in Table VI provide no evidence for a significant link between *C/P VOLUME* and the cross-section of expected returns. 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 emanating from private information does predict future stock returns. As an alternative to option trading volume, we also examine *C/POI*. This variable is highly insignificant as well.

There are stronger effects from alternative measures of implied volatility spreads. In regression (4), *RVOL-IVOL* carries a negative and statistically significant coefficient, consistent with Bali and Hovakimian (2009). In regressions (1) to (4), the coefficients on risk-neutral skewness, *QSKEW*, are negative and highly significant as well. This result is similar to the pattern of *QSKEW* with the Δ*CVOL* and Δ*PVOL* average return patterns in Table IV, and it also confirms the negative predictive relation between option skew and future stock returns in Xing, Zhang, and Zhao (2010). The highly statistically significant loadings on Δ*CVOL* and Δ*PVOL* in the presence of the negative *QSKEW* and *RVOL-IVOL* coefficients imply that the information in option volatility

[13] This is 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.

innovations is different from the predictive ability of the option skew and the variance risk premium uncovered by previous authors.

Cremers and Weinbaum (2010) investigate how the call-put volatility spread, which is the difference between *CVOL* and *PVOL*, predicts stock returns and they also report in passing the relation between $\Delta CVOL$-$\Delta PVOL$ and stock returns.[14] They do not focus on univariate predictability of $\Delta CVOL$ or $\Delta PVOL$ or unconstrained joint predictability of these variables.[15] 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 to 2005). In the Internet Appendix, we show that the predictability from using $\Delta CVOL$ and $\Delta PVOL$ is robust to different sample periods. Specifically, the full sample 1996 to 2011 is first divided into two subsample periods (January 1996 to December 2003 and January 2004 to December 2011), and then, for additional robustness, it is divided into three subsample periods (January 1996 to December 2000, January 2001 to December 2005, and January 2006 to December 2011). After controlling for firm characteristics, risk, and skewness attributes, the average slope coefficients on $\Delta CVOL$ ($\Delta PVOL$) are positive (negative) and highly significant for all subsample periods including 2001 to 2005.[16]

C. Informed Trading

The model of informed trading in Appendix A makes three predictions associated with the predictability of past changes in option volatilities for stock returns. In particular, the predictability should be greater (1) when past option volatilities have increased contemporaneously with stock prices, (2) when large changes in option volatilities are accompanied by unusually large trading volume in option markets, and (3) when there is large trading volume in both option and stock markets.

[14] The Internet Appendix also shows that controlling for the Cremers and Weinbaum (2010) variable, *CVOL-PVOL*, in the regressions does not affect our main results. We find that the coefficient on *CVOL-PVOL* is positive and statistically significant, consistent with Cremers and Weinbaum, but the coefficients on $\Delta CVOL$ and $\Delta PVOL$ are similar to those reported in Table VI and are highly statistically significant.

[15] We reject the null hypothesis that the average slope coefficients on the changes in call and put implied volatilities are identical, with a t-statistic of 2.17 (p-value = 3%). This implies that $\Delta CVOL$ and $\Delta PVOL$ have significant and different impacts on future stock returns, rejecting the constrained joint predictability of these variables.

[16] In the Internet Appendix, we also present results from the pooled panel regressions for the full sample period. The standard errors of the parameter estimates are clustered by firm and time. The pooled panel regression results indicate that, after controlling for all firm characteristics, risk, and skewness attributes, the slope coefficients on $\Delta CVOL$ ($\Delta PVOL$) are positive (negative) and highly significant, similar to our findings from the Fama-MacBeth regressions reported in Table VI, Panel A.

C.1. Interactions with Past Stock Returns

An informed investor can trade both stock and option markets, so intuitively both markets should respond contemporaneously.[17] The predictability by past $\Delta CVOL$ for future stock returns should be especially strong when stock markets have also moved with $\Delta CVOL$.

In regressions (5) to (8) of Panel A, Table VI, we test whether there is greater predictability by $\Delta CVOL$ and $\Delta PVOL$ when past increases in option volatilities are accompanied by contemporaneous increases in stock returns. We create the variable *PastRetDecile*, which takes values from 1 to 10 for stocks ranked into deciles based on their past one-month returns (*REV*). We then interact this variable with the $\Delta CVOL$ and $\Delta PVOL$ variables. A positive coefficient on the interaction term would provide evidence consistent with informed trading taking place in both option and stock markets.

We find that this is indeed the case. In each regression (5) to (8), the average slope coefficients on the $\Delta CVOL \times PastRetDecile$ interaction terms are positive with t-statistics above 2.2. Thus, $\Delta CVOL$ predictability is strongest in stocks that have contemporaneously experienced increases in price over the previous period. This result suggests that informed investors can also trade stocks, the call option prices feedback into stock prices, or both. The coefficients on $\Delta PVOL \times PastRetDecile$ are also positive, but the individual coefficients on $\Delta PVOL$ and *REV* are themselves negative. Hence, the positive coefficient on $\Delta PVOL \times PastRetDecile$ is also consistent with the model's prediction that, when investor demand for both stocks and options is high, the cross-market predictability of options to stocks is enhanced.

C.2. Option Volume

We further investigate informed trading in Panel B of Table VI by focusing on where trading takes place. We run cross-sectional regressions with the following regressors:[18]

$$\Delta CVOL_{i,t}^{HighCallVol} = \left\{ \begin{array}{ll} \Delta CVOL_{i,t} & \text{if } \Delta Call\,Volume > Median \\ 0 & \text{otherwise} \end{array} \right\}, \tag{4}$$

[17] The demand-based option pricing models of Bollen and Whaley (2004) and Garleanu, Pedersen, and Poteshman (2009) 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 noninstantaneous response of the underlying stock market. Some rational and behavioral models explain this delayed reaction including information immobility (Van Nieuwerburgh and Veldkamp (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, for example, Hong and Stein (1999)). Our model in Appendix A shows that the action of informed traders can produce joint option market to stock market predictability, and vice versa, in a noisy rational expectations model.

[18] 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.

$$\Delta CVOL_{i,t}^{LowCallVol} = \left\{ \begin{array}{ll} \Delta CVOL_{i,t} & \text{if } \Delta Call\ Volume < Median \\ 0 & \text{otherwise} \end{array} \right\},$$

$$\Delta PVOL_{i,t}^{HighPutVol} = \left\{ \begin{array}{ll} \Delta PVOL_{i,t} & \text{if } \Delta Put\ Volume > Median \\ 0 & \text{otherwise} \end{array} \right\},$$

$$\Delta PVOL_{i,t}^{LowPutVol} = \left\{ \begin{array}{ll} \Delta PVOL_{i,t} & \text{if } \Delta Put\ Volume < Median \\ 0 & \text{otherwise} \end{array} \right\},$$

which partition $\Delta CVOL$ and $\Delta PVOL$ into whether call or put volatilities occur with relatively high or low option trading volume based on the median change in option trading volume. Stocks with above-median changes in call option trading volume are in the High *Call Volume* group, whereas stocks with below-median changes in call option trading volume are in the Low *Call Volume* group. Similarly, stocks with above- (below-) median changes in put option trading volume are in the High (Low) *Put Volume* group.

The regressions with the variables in equation (4) nest those in the standard regression (3). For example, since $\Delta CVOL_{i,t}^{\text{High Call Vol}} + \Delta CVOL_{i,t}^{\text{Low Call Vol}} = \Delta CVOL_{i,t}$, a regression of

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

nests the first regression, where the $\Delta CVOL$ coefficient does not vary with option trading volume,

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

and $\lambda_{1,t} = \lambda_{1,t}^{HighCallVol} = \lambda_{1,t}^{LowCallVol}$. We expect that, when changes in option volatilities are accompanied by unusually high option volume, the predictability from the option to the stock market should be stronger, all else equal.

We report the estimates of the asymmetric regressions in Panel B of Table VI. Regression (4) uses the same cross-sectional control variables as Panel A, but we do not report them for brevity. The average slope coefficients on $\Delta CVOL_{i,t}^{HighCallVol}$ and $\Delta CVOL_{i,t}^{LowCallVol}$ are economically and statistically different from each other, with values of 2.87 and 1.24, respectively. We reject the hypothesis that the coefficients are equal with a t-statistic of 2.14, suggesting that the strongest predictability of call option volatility innovations is found when these are accompanied by greater than usual call option volume. This result is consistent with informed investors buying call options, leading to increases in call volatilities that predict future stock price appreciation.

Similarly, we find that the average slopes on $\Delta PVOL_{i,t}^{HighPutVol}$ and $\Delta PVOL_{i,t}^{LowPutVol}$ are different, with values of -1.58 and -0.37, respectively.

We reject the hypothesis that the coefficients are equal with a t-statistic of 2.33, which is consistent with informed investors who have high-quality, sizeable information that stocks are trending down buying puts, and with the price discovery 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. The effect of asymmetry is somewhat stronger on the put side than on the call side.

In regressions (3) and (4) in Panel B of Table VI, 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, and the results are even stronger (p-value of 0.40%) compared to testing without all controls (p-value of 2.78%). Moreover, the point estimates in regression (4) on $\Delta CVOL_{i,t}^{HighCallVol}$ and $\Delta CVOL_{i,t}^{LowCallVol}$ are 3.72 and 2.51, respectively, implying a 48% higher impact of $\Delta CVOL$ when call option volatility innovations are accompanied by greater-than-usual call option volume. Similarly, the average slopes on $\Delta PVOL_{i,t}^{HighPutVol}$ and $\Delta PVOL_{i,t}^{LowPutVol}$ are -3.38 and -1.27, respectively, implying a doubling of the impact of $\Delta PVOL$ when put option volatility innovations are accompanied by larger-than-usual put option volume. When we include both call and put volatility shocks simultaneously along with the control variables, the effect of asymmetry is again stronger on the put side than on the call side.

C.3. Joint Option and Stock Volume

A final implication of the informed trading model in Appendix A is that we expect to see the strongest predictability of $\Delta CVOL$ and $\Delta PVOL$ for stock returns in stocks whose options experience unusually large trading *and* the underlying stock volumes are large. The aggressive trading of informed investors in both stock and option markets leads to higher volumes in both markets, and subsequently predictable stock returns.

We investigate this prediction in Table VII by forming bivariate portfolios of stocks sorted by $\Delta CVOL$ and $\Delta PVOL$ controlling for each other's effects, and condition on option trading volume and stock volume. In Panel A, we separate stocks each month into two groups based on the median change in call option trading volume. Stocks with above-median changes in call option trading volume are in the High *Call Volume* group and the other stocks are in the Low *Call Volume* group. Similarly, stocks are independently separated into two groups based on the median change in trading volume of individual stocks. Stocks with a higher change in trading volume are in the High *Stock Volume* group and stocks with a lower change in trading volume are in the Low *Stock Volume* group. Then, for stocks in the High *Call Volume* and High *Stock Volume* group and the Low *Call Volume* and Low *Stock Volume* group, we form bivariate decile portfolios of $\Delta CVOL$ controlling for $\Delta PVOL$ along the lines of Section III.B.

Table VII

Bivariate Portfolios of Stocks Sorted by Δ*CVOL* and Δ*PVOL* Conditioned on Changes in Stock, Call Options, and Put Options Trading Volume

In Panel A, for each month, stocks are separated into two groups based on the median change in call option trading volume. Stocks with above-median change in call option trading volume are in the High *Call Volume* group and stocks with below-median change in call option trading volume are in the Low *Call Volume* group. Similarly, stocks with above-median change in trading volume are in the High *Stock Volume* group and stocks with below-median change in trading volume are in the Low *Stock Volume* group. Then, for stocks in High *Call Volume* and High *Stock Volume* group and the Low *Call Volume* and Low *Stock Volume* groups, we form bivariate decile portfolios of Δ*CVOL* and Δ*PVOL*. In Panel A, decile portfolios are first formed by sorting the optionable stocks based on Δ*PVOL*. Then, within each Δ*PVOL* decile, stocks are sorted into decile portfolios ranked based on the monthly changes in call implied volatilities (Δ*CVOL*) so that Δ*CVOL1* (Δ*CVOL10*) contains stocks with the lowest (highest) Δ*CVOL*. Panel A presents returns averaged across the 10 Δ*PVOL* deciles to produce decile portfolios with dispersion in Δ*CVOL*, but that contain all Δ*PVOL* values. This procedure creates a set of Δ*CVOL* portfolios with similar levels of Δ*PVOL*, and thus these Δ*CVOL* portfolios control for differences in Δ*PVOL*. In Panel A, 10−1 Return Diff. reports the average raw return difference between Δ*CVOL10* and Δ*CVOL1* after controlling for Δ*PVOL*. FF3 Alpha Diff. reports the 10−1 differences in the three-factor Fama-French (FF3) alphas. In Panel B, stocks are first separated into four groups based on the median change in put options trading volume and the median change in stock trading volume. Then, for stocks in the High *Put Volume* and High *Stock Volume* group and the Low *Put Volume* and Low *Stock Volume* groups, we form bivariate portfolios of Δ*CVOL* and Δ*PVOL*. In Panel B, decile portfolios are first formed by sorting the optionable stocks based on Δ*CVOL*. Then, within each Δ*CVOL* decile, stocks are sorted into decile portfolios ranked based on Δ*PVOL*. Panel B reports the average raw return and FF3 alpha differences between Δ*PVOL10* and Δ*PVOL1* after controlling for Δ*CVOL*.

Panel A: Decile Portfolios of Δ*CVOL* Controlling for Δ*PVOL* Conditioned on the Change in *Call Volume* and the Change in *Stock Volume*

	High *Call Volume* High *Stock Volume* Return	Low *Call Volume* Low *Stock Volume* Return
Low Δ*CVOL*	0.24	0.28
2	0.42	0.60
3	0.57	0.48
4	1.15	0.79
5	1.12	0.84
6	0.95	0.88
7	0.96	1.05
8	1.02	1.06
9	1.14	1.04
High Δ*CVOL*	1.67	1.17
10−1 Return Diff.	1.42	0.89
t-stat.	(5.17)	(2.52)
FF3 Alpha Diff.	1.35	0.87
t-stat.	(4.77)	(2.45)

(Continued)

Table VII—*Continued*

Panel A: Decile Portfolios of $\Delta PVOL$ Controlling for $\Delta CVOL$
Conditioned on the Change in *Put Volume* and the Change in *Stock Volume*

	High *Put Volume* High *Stock Volume* Return	Low *Put Volume* Low *Stock Volume* Return
Low $\Delta PVOL$	1.47	1.37
2	1.22	0.93
3	0.87	1.10
4	1.04	0.94
5	0.81	0.71
6	1.02	0.73
7	1.00	0.94
8	0.49	0.88
9	0.71	0.54
High $\Delta PVOL$	0.26	0.64
10−1 Return Diff.	−1.20	−0.73
t-stat.	(−4.82)	(−2.11)
FF3 Alpha Diff.	−1.26	−0.66
t-stat.	(−5.32)	(−2.13)

Panel A of Table VII shows that, for stocks in the High *Call Volume* and High *Stock Volume* group, the average return and FF3 alpha differences between the lowest and highest $\Delta CVOL$ portfolios are 1.42% and 1.35% per month, respectively, both with highly significant t-statistics above 4.7. The return spreads are also positive and significant for stocks in the Low *Call Volume* and Low *Stock Volume* group, but as expected the economic magnitudes are smaller: the average return and alpha differences between the lowest and highest $\Delta CVOL$ portfolios are 0.89% and 0.87% per month, with t-statistics of 2.52 and 2.45, respectively. These results indicate that the predictive power of $\Delta CVOL$ is stronger among firms whose option and stock volume are larger.

In Panel B of Table VII, we perform a similar exercise for stocks, separating them into two groups based on the median change in put trading volume and the median change in stock volume. For stocks in the High *Put Volume* and High *Stock Volume* group and the Low *Put Volume* and Low *Stock Volume* group, we form bivariate decile portfolios of $\Delta PVOL$ controlling for $\Delta CVOL$. For stocks in the High *Put Volume* and High *Stock Volume* group, the average return and FF3 alpha differences between the lowest and highest $\Delta PVOL$ portfolios are −1.20% and −1.26% per month, with highly significant t-statistics of −4.82 and −5.32, respectively. Although the return and alpha spreads are negative and significant for stocks in the Low *Put Volume* and Low *Stock Volume* group, the economic magnitudes are smaller in absolute value: the average return and alpha differences between the lowest and highest $\Delta PVOL$ portfolios are −0.73% and −0.66% per month, with t-statistics above 2.1 in absolute terms.

These results show that $\Delta PVOL$ predictability is also stronger among firms whose option and stock volume are larger.

D. Systematic versus Idiosyncratic Volatility Innovations

Call and put implied volatilities contain both systematic and idiosyncratic components. The predictive power of $\Delta CVOL$ and $\Delta PVOL$ could be due to these variables reflecting news in systematic risk, idiosyncratic components, or both.

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

$$\sigma_{i,t}^2 = \beta_{i,t}^2 \sigma_{m,t}^2 + \sigma_{\varepsilon,i,t}^2, \tag{5}$$

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.

D.1. 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

$$\begin{aligned} CVOL_{i,t}^{sys} &= \beta_{i,t}\sigma_{m,t}, \\ CVOL_{i,t}^{idio} &= \sigma_{\varepsilon,i,t} = \sigma_{i,t} - \beta_{i,t}\sigma_{m,t}, \end{aligned} \tag{6}$$

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 versus 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 $\Delta CVOL^{sys}$, $\Delta PVOL^{sys}$, $\Delta CVOL^{idio}$, and $\Delta PVOL^{idio}$ on the cross section of stock returns. As expected, the cross-sectional correlation of the innovations in the systematic component of volatilities, $\Delta CVOL^{sys}$ and $\Delta PVOL^{sys}$, is very high at above 0.99, whereas the correlation between the idiosyncratic terms, $\Delta CVOL^{idio}$ and $\Delta PVOL^{idio}$, is much lower at 0.86.

In Table VIII, we break up the innovations of $\Delta CVOL$ and $\Delta PVOL$ into systematic and idiosyncratic components while controlling for the usual risk characteristics. Due to the extremely high correlation between the systematic $\Delta CVOL^{sys}$ and $\Delta PVOL^{sys}$ terms, we include only one term in each regression. In the left panel of Table VIII, we decompose the systematic and idiosyncratic

Table VIII

Predicting Returns by Systematic and Idiosyncratic Volatility Shocks

This table presents average slope coefficients and their Newey-West t-statistics in parentheses from the Fama-MacBeth (1973) cross-sectional regressions in equation (3). 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 (6) 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. The last row reports the average R^2 values and their Newey-West (1987) t-statistics in parentheses.

	Physical Measure of Market Beta				Risk-Neutral Measure of Market Beta			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta CVOL^{sys}$	−0.1994	−0.2470			−0.0053	−0.0058		
	(−0.31)	(−0.40)			(−0.45)	(−0.49)		
$\Delta CVOL^{idio}$	3.7376	3.7246	3.7376	3.7246	3.6147	3.5197	3.6007	3.5274
	(7.26)	(7.22)	(7.26)	(7.22)	(4.48)	(4.23)	(4.46)	(4.22)
$\Delta PVOL^{sys}$			−0.1709	−0.2027			−0.0027	−0.0054
			(−0.27)	(−0.33)			(−0.47)	(−0.47)
$\Delta PVOL^{idio}$	−3.8647	−3.9927	−3.8647	−3.9927	−4.0196	−4.0340	−4.0102	−4.0152
	(−7.18)	(−7.74)	(−7.18)	(−7.74)	(−4.48)	(−4.42)	(−4.47)	(−4.40)
BETA	0.0181	0.0140	0.0041	−0.0021	0.0487	0.0539	0.0483	0.0534
	(0.21)	(0.11)	(0.05)	(−0.02)	(0.66)	(0.71)	(0.65)	(0.70)
SIZE	−0.0990	−0.0558	−0.0990	−0.0558	−0.0961	−0.0874	−0.0951	−0.0866
	(−1.30)	(−0.60)	(−1.30)	(−0.60)	(−1.12)	(−1.01)	(−1.10)	(−1.00)
BM	0.3057	0.3405	0.3057	0.3405	0.3568	0.3621	0.3561	0.3610
	(2.76)	(2.56)	(2.76)	(2.56)	(3.23)	(3.24)	(3.23)	(3.24)
MOM	−0.0007	−0.0012	−0.0007	−0.0012	−0.0002	−0.0004	−0.0003	−0.0004
	(−0.19)	(−0.31)	(−0.19)	(−0.31)	(−0.06)	(−0.09)	(−0.06)	(−0.09)
ILLIQ	0.1460	0.1269	0.1460	0.1269	0.0494	0.0456	0.0492	0.0458
	(1.33)	(1.19)	(1.33)	(1.19)	(0.29)	(0.27)	(0.29)	(0.27)
REV	−0.0200	−0.0180	−0.0200	−0.0180	−0.0248	−0.0244	−0.0247	−0.0244
	(−2.48)	(−2.14)	(−2.48)	(−2.14)	(−2.78)	(−2.71)	(−2.77)	(−2.71)

(Continued)

Table VIII—*Continued*

	Physical Measure of Market Beta				Risk-Neutral Measure of Market Beta			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RVOL	−0.7432		−0.7432		−0.2583		−0.2644	
	(−1.28)		(−1.28)		(−0.57)		(−0.59)	
C/P VOLUME	−0.0012	0.0044	−0.0012	0.0044	−0.0142	−0.0118	−0.0135	−0.0110
	(−0.03)	(0.10)	(−0.03)	(0.10)	(−0.25)	(−0.21)	(−0.24)	(−0.19)
C/P OI	0.0682	0.0679	0.0682	0.0679	0.0841	0.0829	0.0826	0.0811
	(1.25)	(1.21)	(1.25)	(1.21)	(1.20)	(1.17)	(1.18)	(1.15)
RVOL-IVOL		−0.6410		−0.6410		−0.5705		−0.5725
		(−2.24)		(−2.24)		(−1.31)		(−1.31)
QSKEW	−2.3888	−2.2752	−2.3888	−2.2752	−0.7558	−0.9028	−0.7344	−0.8859
	(−4.40)	(−4.07)	(−4.40)	(−4.07)	(−0.75)	(−0.80)	(−0.73)	(−0.78)
R^2	9.55%	8.86%	9.55%	8.86%	12.26%	12.15%	12.26%	12.14%
	(10.97)	(11.19)	(10.97)	(11.19)	(11.64)	(11.58)	(11.64)	(11.58)

components using real measure betas. The panel shows that the coefficients on $\Delta CVOL^{idio}$ are positive, at around 3.7, and statistically significant with t-statistics above 7.0. The coefficients on $\Delta PVOL^{idio}$ are approximately -3.9 with t-statistics around -7.0. The positive coefficients on $\Delta CVOL^{idio}$ and the negative coefficients on $\Delta PVOL^{idio}$ are reminiscent of the positive and negative coefficients on $\Delta CVOL$ and $\Delta PVOL$, respectively, in Panel A of Table VI. The coefficients on the systematic components are negative, but statistically insignificant. Clearly, it changes in the idiosyncratic volatility components that drive the predictability.

D.2. Risk-Neutral Betas

We next examine betas estimated using option prices, which we term risk-neutral betas. Christoffersen, Jacobs, and Vainberg (2008), among others, argue that betas computed from option prices contain different information from betas estimated from stock returns. Following Duan and Wei (2009), we compute 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 relation

$$Skew_{i,t} = \beta_{i,t}^{3/2} Skew_{m,t}, \tag{7}$$

where the risk-neutral measures of skewness are estimated following Bakshi, Kapadia, and Madan (2003). We provide further details in Appendix B. The volatility innovations for the systematic and idiosyncratic components are computed using equation (6), 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 0.91.

The right-hand panel in Table VIII reports the results of the systematic versus idiosyncratic decomposition using risk-neutral betas. We again observe that the coefficients on the systematic components on $\Delta CVOL^{sys}$ and $\Delta PVOL^{sys}$ are statistically insignificant. The coefficient on $\Delta CVOL^{idio}$ is around 3.5, with t-statistics above 4.0 and the coefficient on $\Delta PVOL^{idio}$ is approximately -4.0, with t-statistics of -4.4. These coefficients are very similar to those 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 $\Delta CVOL$ and $\Delta PVOL$ is arising from informed investors placing trades in option markets, these investors tend to have better information about future company-specific news or events than about how these stocks are reacting to systematic factor risk.

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

So far, we have examined the predictability of past option volatility changes for future stock returns. According to the informed trading model in Appendix A, there should also be reverse predictability from stocks to options, so past stock returns should also predict option volatilities. We are 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 simple proxy for new arrivals in stock markets.

A. Predicting Option and Realized Volatilities

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

$$\begin{aligned} \Delta CVOL_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} Alpha_{i,t} + \lambda_{2,t} Controls + \varepsilon_{i,t+1}, \\ \Delta PVOL_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} Alpha_{i,t} + \lambda_{2,t} Controls + \varepsilon_{i,t+1}, \\ \Delta CVOL_{i,t+1} - \Delta PVOL_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} Alpha_{i,t} + \lambda_{2,t} Controls + \varepsilon_{i,t+1}, \\ \Delta RVOL_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} Alpha_{i,t} + \lambda_{2,t} Controls + \varepsilon_{i,t+1}, \end{aligned} \tag{8}$$

where the dependent variables, $\Delta CVOL$ and $\Delta PVOL$, denote the monthly changes in call and put implied volatilities for stock i over month t to $t+1$, $\Delta RVOL$ denotes the monthly change in realized volatility of stock i over month t to $t+1$, and *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).[19] The monthly alphas are computed by summing the daily idiosyncratic returns over the previous month. To test the significance of information flow from the stock to the option market, the cross section of implied volatility changes over month $t+1$ is regressed on the abnormal returns of individual stocks in month t.

The first two specifications in equation (8) examine how call and put volatilities over the next month respond to excess returns over the previous month. The third cross-sectional regression in equation (8) looks at how call volatilities move relative to put volatilities. Since call and put volatilities tend to move in unison for the same firm, predicting the spread between put and call implied volatilities, $\Delta CVOL$-$\Delta PVOL$, attempts to control for the common component in both call and put volatilities. The final regression in (8) predicts future firm-level realized volatilities in the cross section.

We deliberately do not use option returns as the dependent variable in equation (8). Option returns exhibit marked skewness and have pronounced

[19] As shown in the Internet Appendix, almost identical results are obtained when past month stock returns are used.

nonlinearities from dynamic leverage, making statistical inference difficult (see, among others, Broadie, Chernov, and Johannes (2009), Chaudhri and Schroder (2009)). By focusing on implied volatilities, we avoid many of these inference issues. 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.[20]

Table IX 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 for which 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 (put) volatilities by 4.15% (2.32%), on average, with a highly significant t-statistic of 10.58 (6.03). High book-to-market stocks tend to exhibit decreases in implied volatilities next period, with a coefficient of -0.20 for call volatility changes and -0.13 for put volatility changes. There is a statistically significant momentum effect for predicting call implied volatilities, but the coefficient is very small. The illiquidity effect is strong for call, but weaker and insignificant for put volatility changes. With the exception of *BETA* and *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* 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 (see, for example, Roll, Schwartz, and Subrahmanyam (2009)). Finally, changes in call (put) implied volatilities tend to be lower (higher) for options for which the smile exhibits more pronounced negative skewness.

Interestingly, Table IX shows that some variables differentially predict call and put volatilities. Note that call and put volatilities are correlated (Table I shows a cross-sectional correlation of 0.58), but there is some independent movement. In the $\Delta CVOL$-$\Delta PVOL$ column, *Alpha* and *RVOL* increase call volatilities more than put volatilities, while book-to-market decreases call volatilities less than put volatilities.

Finally, the last column of Table IX shows that there is pronounced predictability in the cross section of realized volatilities. This predictability in realized volatilities is the *opposite* of the predictability in implied volatilities. In particular, the coefficient on *Alpha* in the $\Delta CVOL$ regression is 4.15, whereas that in the $\Delta RVOL$ regression is -14.32, which is approximately 3.5 times

[20] Our focus on cross-sectional predictability of implied volatilities is very different from most studies in the literature focusing on time-series relations like Harvey and Whaley (1992), who examine the predictability of the S&P 100 index option volatility, Christensen and Prabhala (1998) and Chernov (2007), who also focus on the aggregate index level, and Bollen and Whaley (2004), who investigate time-series predictability of 20 individual options but focus only on net buying pressure.

Table IX

Predicting the Cross Section of Implied and Realized Volatilities

This table presents coefficients from the cross-sectional regression in equation (8), which predicts changes in options' implied volatilities and changes in realized volatility. The daily alphas are estimated based on the CAPM using daily return observations over the previous month. The monthly *ALPHA* is calculated by summing the daily alphas in a month. The dependent variables are, respectively, the next-month change in call volatility, $\Delta CVOL$, the next-month change in put volatilities, $\Delta PVOL$, the change in call volatility relative to put volatility, $\Delta CVOL$-$\Delta PVOL$, and the change in realized volatility, $\Delta RVOL$. 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 (*BM*), momentum (*MOM*), illiquidity (*ILLIQ*), realized volatility (*RVOL*), change in call open interest (ΔOI^C), change in put open interest (ΔOI^P), and risk-neutral skewness (*QSKEW*). Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1996 to December 2011.

	$\Delta CVOL$	$\Delta PVOL$	$\Delta CVOL$ - $\Delta PVOL$	$\Delta RVOL$
ALPHA	4.1504	2.3155	1.8349	−14.323
	(10.58)	(6.03)	(6.17)	(−10.11)
BETA	−0.0163	0.0482	−0.0645	1.2080
	(−0.51)	(1.04)	(−1.76)	(7.22)
SIZE	−0.0141	−0.0473	0.0332	−3.4680
	(−0.30)	(−1.36)	(0.81)	(−39.35)
BM	−0.2038	−0.1332	−0.0706	−2.4210
	(−3.74)	(−2.72)	(−2.77)	(−6.90)
MOM	0.0016	0.0015	0.0001	0.0103
	(2.12)	(1.96)	(0.31)	(1.36)
ILLIQ	0.1878	0.1563	0.0315	1.1552
	(2.08)	(1.55)	(0.33)	(4.36)
RVOL	−1.2887	−2.0157	0.7270	−60.765
	(−3.77)	(−6.27)	(3.06)	(−36.44)
ΔOI^C	−0.7151	−0.4676	−0.2475	−0.6412
	(−8.63)	(−4.72)	(−2.84)	(−4.42)
ΔOI^P	−0.3003	−0.2350	−0.0654	−0.4230
	(−7.90)	(−5.01)	(−1.60)	(−4.53)
QSKEW	26.606	−4.0769	30.683	−5.1930
	(14.62)	(−2.03)	(10.53)	(−2.63)
R^2	7.98%	5.56%	7.55%	34.30%
	(15.75)	(11.60)	(13.98)	(41.83)

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 most of the other stock characteristics have the same sign for both implied and realized volatilities.

The findings that past stock returns predict option volatilities, that the predictability of call volatilities is stronger than that of put volatilities, and that option volatility is forecasted to increase, while realized volatility decreases are all consistent with the model of informed trading in Appendix A. Intuitively, informed traders with good news trade both call options, which increase implied volatilities, and stocks. Prices do not perfectly adjust this period, leading stock prices, and consequently call option prices, to increase in the next period. This leads to past high stock alphas predicting call option volatilities. The action of informed trading this period resolves some uncertainty. Therefore, future realized volatility decreases over the following period. The predictability of call option volatilities is stronger than put volatilities for a given alpha because, for good news released today, stock prices continue to adjust upward in the next period. This causes the price of calls to increase, and the price of puts to decrease. There is continued adjustment, but the stock has already moved toward its fundamental value. This partial adjustment today causes next period's adjustment on the put option to be smaller as the put option delta becomes less negative.

B. Further Economic Investigation

The predictability of option volatilities may be consistent with stories other than informed trading. To investigate this possibility, we form portfolios of option volatilities similar to the portfolio returns constructed in Section III. We focus on predictability by *Alpha*. Table X 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 X reports the same familiar results as Table IX but now in a decile 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 across the extreme decile portfolios are highly statistically significant in all cases.

B.1. 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 overestimate 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). 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). Agents perceive stocks with recent gains to be less risky and thus implied volatility declines.

According to Barberis and Huang (2001), 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

Table X

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. Decile portfolios are formed based on the monthly CAPM alphas, and then the average values are reported for the next-month change in call volatilities ($\Delta CVOL$), the next-month change in call volatilities relative to put volatilities ($\Delta CVOL$-$\Delta PVOL$), and the next-month change in realized volatilities ($\Delta RVOL$). 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 Panel A of Table VI without $\Delta CVOL$ or $\Delta PVOL$. 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 the liquidity of individual stocks is 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 (1987) *t*-statistics are given in parentheses. The sample period is January 1996 to December 2011.

Panel A: All Stocks

	$\Delta CVOL$	$\Delta CVOL$-$\Delta PVOL$	$\Delta RVOL$
Low *Alpha*	−1.53	−0.82	−1.70
2	−0.54	−0.39	3.20
3	−0.37	−0.12	3.20
4	−0.12	−0.11	2.77
5	−0.04	−0.04	2.29
6	0.20	0.19	1.67
7	0.30	0.23	1.21
8	0.52	0.22	−0.24
9	0.60	0.39	−2.18
High *Alpha*	0.59	0.66	−12.78
10−1 Diff.	2.12	1.48	−11.08
t-stat.	(8.62)	(7.01)	(−11.34)

Panel B: High Cross-Sectional Predictability versus Low Cross-Sectional Predictability

	Stocks with Low Cross-Sectional Predictability			Stocks with High Cross-Sectional Predictability		
	$\Delta CVOL$	$\Delta CVOL$-$\Delta PVOL$	$\Delta RVOL$	$\Delta CVOL$	$\Delta CVOL$-$\Delta PVOL$	$\Delta RVOL$
Low *Alpha*	−1.46	−0.83	0.14	−1.63	−0.74	−5.10
2	−0.38	−0.50	6.32	−0.80	−0.28	−0.29
3	−0.25	−0.29	6.13	−0.53	−0.10	0.33
4	0.15	−0.07	5.82	−0.41	−0.19	0.24
5	0.13	−0.02	5.14	−0.05	0.06	0.07
6	0.50	0.21	4.58	−0.05	0.17	−0.62
7	0.52	0.17	3.83	0.13	0.20	−1.00
8	0.88	0.42	2.18	0.16	0.15	−2.08
9	0.90	0.49	−0.32	0.42	0.40	−4.25
High *Alpha*	0.64	0.73	−12.14	0.40	0.44	−14.11
10−1 Diff.	2.10	1.56	−12.28	2.02	1.18	−9.01
t-stat.	(6.27)	(6.50)	(−10.10)	(9.31)	(6.30)	(−11.17)

(Continued)

Table X—*Continued*

Panel C: High Volatility versus Low Volatility

	Low Volatility Stocks			High Volatility Stocks		
	Δ*CVOL*	Δ*CVOL*-Δ*PVOL*	Δ*RVOL*	Δ*CVOL*	Δ*CVOL*-Δ*PVOL*	Δ*RVOL*
Low *Alpha*	−0.33	−0.45	9.73	−2.16	−1.00	−7.63
2	−0.29	−0.29	6.28	−1.04	−0.65	−0.58
3	−0.14	−0.13	5.31	−0.66	−0.31	−1.11
4	−0.14	−0.16	4.70	−0.37	−0.09	−1.08
5	0.16	0.00	4.12	−0.13	0.05	−1.63
6	0.24	0.16	3.95	0.05	0.25	−2.60
7	0.51	0.27	3.74	0.16	0.36	−4.04
8	0.44	0.19	3.54	0.36	0.39	−5.50
9	0.77	0.34	3.23	0.53	0.51	−8.16
High *Alpha*	0.91	0.33	3.53	0.42	0.68	−20.96
10−1 Diff.	1.24	0.78	−6.20	2.58	1.69	−13.33
t-stat.	(5.56)	(4.54)	(−9.50)	(8.12)	(6.67)	(−10.09)

Panel D: Liquid versus Illiquid Stocks

	Liquid Stocks			Illiquid Stocks		
	Δ*CVOL*	Δ*CVOL*-Δ*PVOL*	Δ*RVOL*	Δ*CVOL*	Δ*CVOL*-Δ*PVOL*	Δ*RVOL*
Low *Alpha*	−1.23	−0.30	−0.65	−1.89	−1.12	−4.02
2	−0.51	−0.17	2.08	−0.65	−0.64	4.22
3	−0.24	−0.14	2.17	−0.45	−0.37	3.83
4	−0.19	−0.11	2.19	−0.24	−0.02	4.22
5	0.03	−0.07	1.57	0.05	−0.11	3.44
6	0.18	0.12	1.18	0.27	0.16	2.73
7	0.38	0.33	0.85	0.25	0.34	0.83
8	0.54	0.24	0.15	0.33	0.53	−0.61
9	0.70	0.26	−1.04	0.63	0.54	−3.78
High *Alpha*	0.79	0.31	−6.86	0.51	0.66	−17.61
10−1 Diff.	2.02	0.61	−6.21	2.40	1.78	−13.59
t-stat.	(6.23)	(4.52)	(−6.87)	(7.79)	(6.98)	(−11.46)

Panel E: High Volatility Uncertainty versus Low Volatility Uncertainty

	Stocks with Low Volatility Uncertainty			Stocks with High Volatility Uncertainty		
	Δ*CVOL*	Δ*CVOL*-Δ*PVOL*	Δ*RVOL*	Δ*CVOL*	Δ*CVOL*-Δ*PVOL*	Δ*RVOL*
Low *Alpha*	0.18	−0.23	2.96	−2.39	−1.10	−5.68
2	0.11	−0.18	3.51	−1.16	−0.54	2.70
3	0.17	0.00	3.26	−0.89	−0.47	2.76
4	0.20	−0.09	2.97	−0.81	−0.13	2.30
5	0.34	−0.06	2.57	−0.52	0.03	1.93
6	0.40	0.12	2.25	−0.14	0.14	1.25
7	0.52	0.19	1.96	−0.11	0.29	−0.18
8	0.58	0.15	1.21	0.05	0.46	−2.33
9	0.91	0.26	0.61	0.45	0.63	−4.97
High *Alpha*	1.16	0.22	−3.85	0.29	0.84	−18.55
10−1 Diff.	0.98	0.45	−6.82	2.68	1.94	−12.88
t-stat.	(5.12)	(3.78)	(-9.70)	(8.63)	(7.36)	(−10.64)

take the 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* deciles in Panel A, Table X. This is not the case. The average change in *DISP* decreases from 0.097 to −0.165 as we move from the Low to High *Alpha* deciles. That is, the $\Delta DISP$ goes in the opposite direction from the $\Delta CVOL$ numbers. This casts doubt on a behavioral overreaction story for volatilities, at least as articulated by Barberis and Huang.

B.2. Other Rational Explanations

Predictability of option volatilities can arise from other rational channels. Lo and Wang (1995), for example, show that predictable returns 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 for cross-sectional predictability, which we examine. All else being equal, when the underlying stock return is more predictable, current option volatilities should decline. Since the predictable components of both 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 conjecture, we divide the sample into two groups of stocks based on the absolute residuals from the cross-sectional regressions of returns. We use the same control variables in Panel A of Table VI without $\Delta CVOL$ and $\Delta PVOL$. Since our objective is to determine whether the predictability of future volatilities is different for stocks with high and low predictability, we exclude $\Delta CVOL$ and $\Delta PVOL$ from the first-stage cross-sectional regressions to avoid confounding the predictability of stock returns with the predictability of option volatilities. We divide the stock universe into high and low cross-sectional predictability groups based on the median value of absolute residuals for each month. Panel B of Table X shows that predictability of future implied and realized volatilities is stronger for stocks with low cross-sectional predictability as the 10−1 differences in implied and realized volatilities across the extreme *Alpha* deciles are economically and statistically larger for stocks with low absolute residuals. The difference, however, for the predictability of $\Delta CVOL$ by past *Alpha* is only very slightly stronger for stocks with low cross-sectional predictability. Nevertheless, the overall results are consistent with Lo and Wang (1995): when stock returns are more predictable, the predictability of future volatilities declines.[21]

[21] We also obtain similar results when we measure stock return predictability using time-series predictability measures as opposed to cross-sectional measures in Table X, Panel B. See the Internet Appendix.

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 option portfolios in Panel A of Table X, the change in option call volume increases as we move from the Low to High *Alpha* decile. 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 X, 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 $10-1$ differences in implied and realized volatilities across the extreme *Alpha* deciles 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 X considers liquid and illiquid stocks separately. We find that the predictability is less pronounced in liquid stocks: the $\Delta CVOL$ spread between the Low *Alpha* and High *Alpha* portfolios is smaller, there is less relative movement of call volatilities versus put volatilities, and there is also weaker predictability of future realized volatility.

Finally, we divide stocks into two groups based on median volatility uncertainty, where volatility uncertainty is measured as the variance of daily changes in call implied volatilities in a month. Stocks with high variance of $\Delta CVOL$ (or high volatility uncertainty) are harder to hedge, all else being equal, than stocks with low volatility uncertainty. Hence, Panel E of Table X shows that the predictability is more pronounced in stocks with high volatility uncertainty: the $\Delta CVOL$, $\Delta CVOL$-$\Delta PVOL$, and $\Delta RVOL$ 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 may be related to the lack of option hedgeability.

V. Conclusion

We document the ability of option volatilities to predict the cross section of future stock returns, and the ability of the cross section of stock returns to predict future option volatilities. Specifically, stocks with past large innovations in call option implied volatilities positively predict future stock returns, while stocks with previous large changes in put option implied volatilities predict low stock returns. When decile portfolios are formed based on past first differences in call volatilities, the spread in average returns and alphas between the first and tenth portfolios is approximately 1% per month and highly significant. After accounting for the effect of call implied volatilities, the average raw and risk-adjusted return differences between the extreme decile portfolios of put volatility changes are greater than 1% per month and also highly significant. This cross-sectional predictability of stock returns from call and put volatility innovations is robust to controlling for the usual firm characteristics and risk factors drawn from both equity and option markets, and appears in subsample periods including the most recent financial crisis. While strongest for the next-month horizon, this predictability persists up to six months for call and up to four months for put volatility changes.

We introduce a noisy rational expectations model of informed trading that contemporaneously moves both option and stock markets. Predictability from option to stock markets, and from stock markets to option markets, arises from informed trading. The model also suggests that the predictability should be stronger when trading volumes in stock and option markets are higher. We find empirical evidence consistent with the model's predictions. We also find that it is changes in the idiosyncratic, not systematic, components of implied volatilities that drive this predictability, implying that investors trading first in option markets have better information about firm-specific news or events.

In the other direction of predictability from stock market variables 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 call (put) option implied volatilities to increase by around 4% (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 comovements 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.

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Appendix A

Model of Informed Stock and Option Trading

This appendix presents a noisy rational expectations economy with stock and option securities. The underlying intuition of the model is that informed traders choose to trade in both stock and option markets, but the extent of their trading depends on the amount of noise trading present in the separate markets. The prices of the stock and options are linked through the actions of a market dealer, who can arbitrage between the two markets. Prices move through the trades of the informed investor, but they do not fully adjust to a fully revealing rational expectations economy. Thus, there is predictability from option prices to stock returns, and from stock returns to option prices. The model also predicts that, when noise traders' demand of both stocks and options is high, the cross-market predictability of options to stocks (and vice versa) is enhanced.

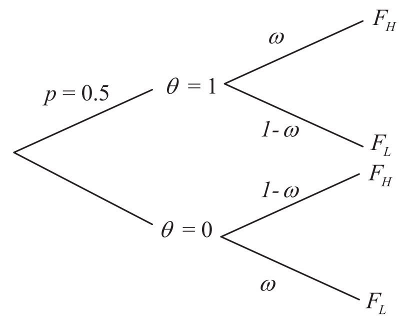
The two most closely related models are by Easley, O'Hara, and Srinivas (1998) and Garleanu, Pedersen, and Poteshman (2009). Like Easley, O'Hara, and Srinivas (1998), we have informed traders, noise traders, and a market dealer. We also allow informed traders to place orders in the equity market, option market, or both. Easley, O'Hara, and Srinivas show that, if at least some informed investors choose to trade in options before trading in underlying stocks, option prices will predict future stock price movements. Informed traders may find it easier to hide their trades in equity markets, in which case stock markets will lead option markets. In the Easley, O'Hara, and Srinivas model, the fundamental value of the stock is exogenously given and trades occur at bid-ask spreads determined by a market maker. Like standard microstructure models, the bid-ask spreads reflect adverse selection. In our model, the price of the stock is endogenously determined and predictability of options to stock returns, and stock characteristics to option prices, occurs jointly because we allow for simultaneous, rather than sequential, trading in both stock and option markets. Garleanu, Pedersen, and Poteshman (2009) develop an equilibrium model where the end-user demand of options affects option prices. They take the stock price as exogenous and do not model asymmetric information.

A.1. Economy

The firm is born at date 0, investors trade the stock at date 1, and the firm's cash flows F are realized at date 2. The unconditional distribution of F is binomial where $F = F_H$ with probability 0.5 and $F = F_L$ with probability 0.5. We denote the stock prices at time 0 and 1 as S_0 and S_1, respectively.

We assume that there is a call option written on the stock. The strike price of the call is K, $F_L < K < F_H$, and the call matures at date 2. We denote the call prices at time 0 and 1 as C_0 and C_1, respectively. The payoff of the call at time 2 is $C_2 = (F - K)^+$.

There are informed agents, uninformed agents, and a market dealer, all with CARA utility with risk aversion γ. Informed agents observe a signal, θ, just before date 1. The signal θ takes value one with probability 0.5 and value zero with probability 0.5. Conditional on θ, F takes the distribution



where the parameter ω, $\frac{1}{2} < \omega < 1$, represents the quality of the signal θ. We denote $p(\theta) = \omega\theta + (1-\omega)(1-\theta)$, which implies that $p(\theta) = 1 - p(1-\theta)$.

The informed traders trade both the stock and the call option, and we denote their demands for the stock and call option by q_I and d_I, respectively. The representative market dealer also trades both the stock and the call option, and her demands are q_D and d_D, respectively. There are uninformed agents in both stock and option markets, and they cannot trade across markets. We denote uninformed stock demands by $z \sim N(0, \sigma_z^2)$, and uninformed option demands by $v \sim N(0, \sigma_v^2)$, where v and z are independent. We assume that the call option is in zero net supply and there is one share outstanding of the stock. Hence, the market-clearing conditions for the stock and call option markets are

$$q_I + q_D + z = 1, \tag{A1}$$

and

$$d_I + d_D + v = 0. \tag{A2}$$

A.2. Equilibrium

First consider the case in which the informed trader receives no signal. We also assume that, at date 0, there are no demand shocks in either market. Since the informed trader and market dealer are identical, they buy half a stock each at price S_0 and there is no trading in the option market.

After the informed trader receives the signal just prior to time 1, the informed trader solves

$$\max_{q_I, d_I} E\left[-\frac{1}{\gamma} \exp(-\gamma W_I) \middle| \theta \right] \tag{A3}$$

subject to

$$q_I S_1 + d_I C_1 = \frac{1}{2} S_1, \tag{A4}$$

where $W_I = (F - S_1)q_I + (C_2 - C_1)d_I$. Taking the first order conditions (FOC) with respect to q_I and d_I gives

$$q_I(F_H - F_L) + d_I(F_H - K) = -\frac{1}{\gamma}\log\left(\frac{1-p(\theta)}{p(\theta)}\frac{S_1 - F_L}{F_H - S_1}\right), \tag{A5}$$

and

$$C_1 = \frac{F_H - K}{F_H - F_L}(S_1 - F_L). \tag{A6}$$

Note that the call option is a linear security, which results from the binomial distribution of the stock cash flows. If we were to specify a put option in place of a call option, the results would be equivalent.

The derivation for the optimal demand for the market maker is similar, except that the market maker cannot observe the signal θ. We assume that the market maker has unlimited wealth, so she has no budget constraint. The FOC for the market maker's optimization is

$$q_D(F_H - F_L) + d_D(F_H - K) = -\frac{1}{\gamma}\log\left(\frac{S_1 - F_L}{F_H - S_1}\right). \tag{A7}$$

We can sum equations (A5) and (A7) to derive the price of the stock as

$$S_1(\theta, z, v) = \frac{G(\theta, z, v)}{1 + G(\theta, z, v)}F_H + \frac{1}{1 + G(\theta, z, v)}F_L, \tag{A8}$$

where the function $G(\theta, z, v)$ is given by

$$G(\theta, z, v) = \sqrt{\frac{p(\theta)}{1 - p(\theta)}}\exp\left(-\frac{\gamma}{2}\left((1 - z)(F_H - F_L) - v(F_H - K)\right)\right). \tag{A9}$$

The call option price is determined from equation (A6). Finally, we can obtain the informed and market maker demands q_I, d_I, q_D, and d_D using the market-clearing conditions in equation (A4) and the FOC in equation (A5).

This analysis assumes that the dealer does not anticipate that the informed trader is going to receive a signal. We can address the case in which both the trader and the dealer anticipate that the trader will receive a signal by subgame perfect equilibrium. Upon the arrival of a signal, the previous solution is still valid. The only difference is that the budget constraint of the informed trader is changed to $q_I S_1 + d_I C_1 = q_{I0} S_1 + d_{I0} C_1$, where q_{I0} and d_{I0} are the informed trader's demand of the stock and option, respectively, at time 0. In this setting, we still assume that, at time 0, there are no noise trader shocks in the stock and option markets. Given the optimal trading strategy and the price of the stock and the option contingent upon the signal, we can derive the expected utility of the trader at time 0. The FOC with respect to q_{I0} and d_{I0} are always zero, so the optimal q_{I0} and d_{I0} are zero if we assume that shorting is not permitted and initial wealth is zero. This is intuitive because the trader knows that he is going to receive an informative signal, so he prefers to wait until the signal is released to trade. Hence, even if the trader and dealer anticipate the arrival of the signal, the results will be the same as the equilibrium discussed, except equilibrium demand will change because the budget constraint of the informed trader is changed to $q_I S_1 + d_I C_1 = 0$ compared to the previous budget constraint of $q_I S_1 + d_I C_1 = \frac{1}{2} S_1$.

A.3. Option-Stock Cross-Predictability

Our empirical results show that the change in call option volatility over the previous month is positively correlated with stock returns over the next month. In the context of the model, this translates into an increase in the call option's price at date 1 being positively correlated with the return of the stock from date 1 to date 2. Call option prices positively predict future stock returns if $\text{cov}(F - S_1, C_1) > 0$. We also find that increases in stock prices over the previous month are positively correlated with option volatilities over the next month. We can interpret this result in the model by examining the sign of $\text{cov}(C_2 - C_1, S_1)$.

The sign of $\text{cov}(F - S_1, C_1)$ is equal to the sign of

$$\text{cov}(F, S_1) - \text{var}(S_1) = E\left[(F - E(F) - S_1 + E(S_1))(S_1 - E(S_1))\right]. \quad \text{(A10)}$$

We can compute this expectation numerically. Also, given θ, we can compute *(z,v)* such that the inner term of the expectation is equal to zero by solving for $S_1(\theta, z, v) = E(S_1)$.

The sign of $\text{cov}(C_2 - C_1, S_1)$ turns out to be given by the same condition, $S_1(\theta, z, v) = E(S_1)$, since

$$\text{cov}(C_2 - C_1, S_1) = E\left[(C_2 - E(C_2) - C_1 + E(C_1))(S_1 - E(S_1))\right]. \quad \text{(A11)}$$

Using the model, we can examine conditions under which $\text{cov}(F - S_1, C_1) > 0$ and $\text{cov}(C_2 - C_1, S_1) > 0$.

A.4. Realized Volatility

The model also predicts that there will be a negative correlation between realized volatility and the call option price. That is, if changes in the call option predict future stock returns, changes in the call option will predict a decrease in realized volatility. Intuitively, the arrival of information at time 1 shrinks the difference in the stock price between time 1 and time 2 compared to that between time 0 and time 2 because some uncertainty is resolved and priced by the actions of informed traders.

We can compare

$$\text{var}(F - S_1) < \text{var}(F - S_0), \quad \text{(A12)}$$

where we take S_0 as constant. The inequality can be simplified to yield

$$2\text{cov}(F, S_1) - \text{var}(S_1) = \text{cov}(F, S_1) + \text{cov}(F - S_1, S_1) > 0. \quad \text{(A13)}$$

The condition $\text{cov}(F - S_1, S_1) > 0$ is the same condition for the predictability of the stock return from the past call price. Thus, if the stock is predictable by the call option and the current stock price is positively correlated with future cash flows, then the volatility of the stock will decrease. Furthermore, even if the stock is not predictable by the call option, sufficiently high covariance between the current stock price and future cash flows will predict a decreasing volatility of the stock.

A.5. Limitations of the Model

Before we present a numerical example, it is worth noting several limitations of the model. First, in the model, the call price at time 1 is linear in the stock price. This results from assuming a binomial tree of the firm's cash flows F. While analytically tractable, it makes the first implication of the model, $\text{cov}(F - S_1, C_1) > 0$, identical to the stock momentum effect, $\text{cov}(F - S_1, S_1) > 0$. Thus, the predictability of options does not exist after controlling for past stock returns in the binomial setting, contrary to the empirical results in Section IV. With richer cash flow distributions, the call price may not be linear in the stock price, so the predictability of the call will exist after controlling for past stock returns. However, it will be hard to analytically derive the equilibrium prices of calls and stocks with more general distributions.

In the model, there is only a single stock and call option. Our empirical work documents predictability of stock returns from option volatilities, and vice versa, in the cross section. Extending the model to multiple stocks and their call/put options introduces large complexity in analyzing the equilibrium prices and joint predictability. The same intuition, however, will go through when there are multiple stocks. The informed trader receives multiple signals for each stock and trades multiple stocks and options simultaneously. There will be complex interactions resulting from the covariance structure of systematic risk from the stocks. However, similar predictability in our model will apply when the agent receives independent signals of idiosyncratic cash flows, and we consider idiosyncratic returns and option volatility changes. In our empirical work, we control for systematic risk using a wide range of factor loadings and risk characteristics.

A.6. Numerical Example

We take an option with strike $K = E(F)$, which is approximately at the money. We use the parameters $F_H = 103$, $F_L = 97$, $K = 100$, $\omega = 0.7$, $\gamma = 1.5$, and $\sigma_z = \sigma_v = 0.1$. With these parameters, we can compute

$$\text{cov}(F - S_1, S_1) = 0.0352,$$

$$\text{cov}(C_2 - C_1, S_1) = 0.0176.$$

That is, predictability of options to stock returns and stocks to option prices arises jointly. The stock volatility decreases in period 2 as $\mathrm{cov}(F, S_1) + \mathrm{cov}(F - S_1, S_1) = 0.0734$.

Informed investors trade both stocks and calls, and the extent of their trading depends on the amount of noise trading in stock and option markets. As they trade, both stock and option prices at time 1 change. Figure A1 plots the stock and call prices as a function of uninformed demand shocks given a good signal, $\theta = 1$. Panel A graphs the stock price in the solid line as a function of the stock demand shock, z, while we hold the call demand shock at $v = 0$. We plot the stock price as a function of the call demand shock, v, while holding the stock demand shock at $z = 0$ in the dashed line. Panel B repeats the same exercises for the call price. In both cases, as the noise trader presence is larger (higher uninformed demand), prices rise because the informed investor becomes more aggressive in trading, hiding behind the larger uninformed demand.

In Figure A2, we plot a pair of uninformed demand *(z,v)* such that there is no predictability between the call price and future stock returns given a good signal, $\theta = 1$. The same condition is also responsible for inducing predictability between past stock returns and future call prices. These are pairs of *(z,v)* that satisfy the condition in equations (A10) and (A11). We vary the stock demand shock over $[-1.96\sigma_z, 1.96\sigma_z]$.

The pairs of *(z,v)* for which there is no cross option-stock (and vice versa) predictability lie on the downward-sloping line in Figure A2. Given a call demand shock, an increase in stock demand induces an increase in the stock price and by no-arbitrage the call price. To offset the increase in the stock return, the call demand shock has to decrease. Pairs of *(z,v)* for which there is positive covariation, that is, positive joint option-stock predictability relations, lie to the upper right-hand corner of Figure A2. Thus, the model predicts that the predictability of stock returns by option volatilities should be strongest in stocks that experience large call and stock volume. This is borne out in the tests performed in Section IV.B.

A.7. Extension to a Put Option

Because this is a binomial model, the option price is linear in the stock price. We can introduce a put option market similar to the call option market. We now assume that there are noise trader demands in the call market $v_c \sim N(0, \sigma_c^2)$ and noise trader demands in the put market $v_p \sim N(0, \sigma_p^2)$. These demands can be correlated. The informed trader and market dealer can trade the stock, call option, put option, or all three. Denoting u_I and u_D as the demand for the put of the informed trader and the market dealer, respectively, and P_1 as the put price at time 1 with strike K, we have

$$S_1(\theta, z, v_c, v_p) = \frac{G(\theta, z, v_c, v_p)}{1 + G(\theta, z, v_c, v_p)} F_H + \frac{1}{1 + G(\theta, z, v_c, v_p)} F_L,$$

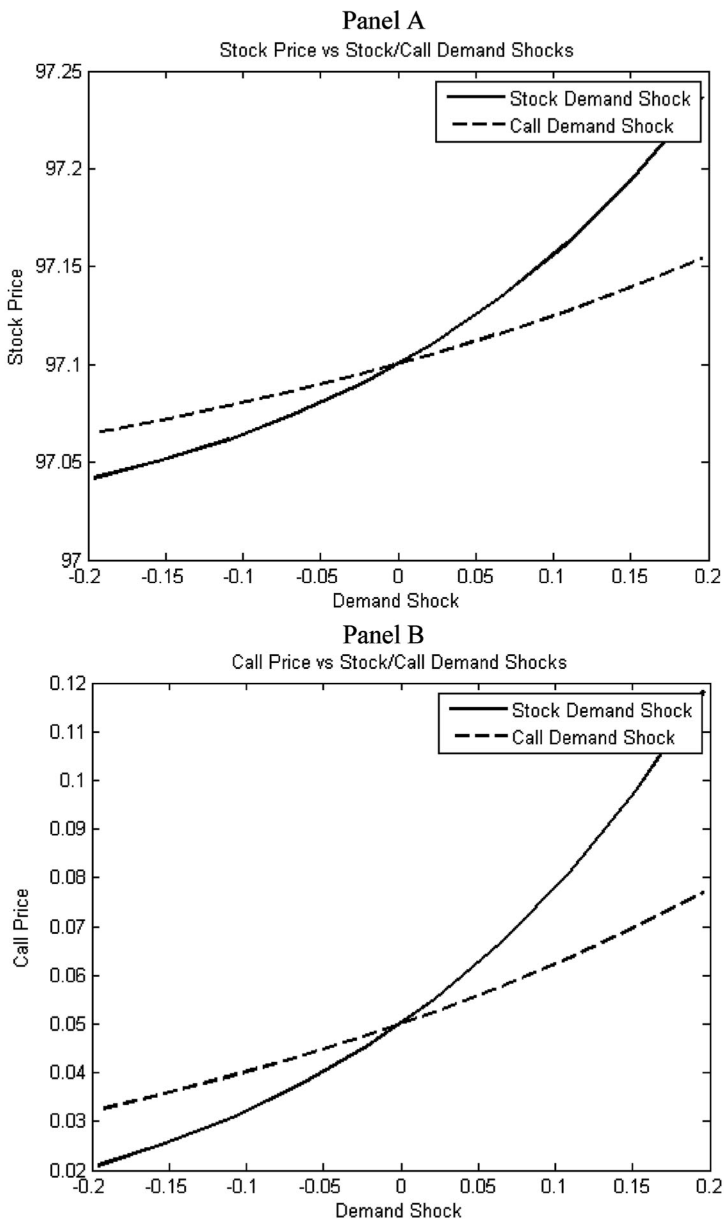


Figure A1. Stock and call prices as a function of uninformed demand shocks. This figure plots stock and call prices as a function of uninformed demand shocks given a good signal, $\theta = 1$. Panel A graphs the stock price in the solid line as a function of the stock demand shock, z, while we hold the call demand shock at $v = 0$. The stock price is plotted as a function of the call demand shock, v, while holding the stock demand shock at $z = 0$ in the dashed line. Panel B repeats the same exercises for the call price. In both cases, as the noise trader presence is larger (higher uninformed demand), prices rise because the informed investor becomes more aggressive in trading, hiding behind the larger uninformed demand.

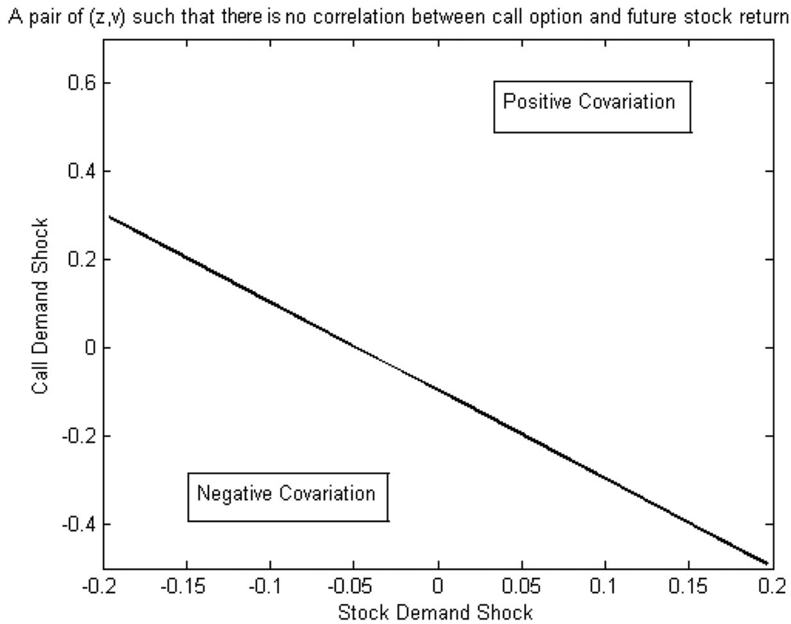


Figure A2. Pairs of call and stock demand shocks generating predictability. We plot pairs of uninformed demand (z,v) such that there is no predictability between the call price and future stock returns given a good signal, $\theta = 1$. The same condition is also responsible for inducing predictability between past stock returns and future call prices. These are pairs of (z,v) that satisfy the condition in equations (A10) and (A11). The stock demand shock varies over $[-1.96\sigma_z, 1.96\sigma_z]$.

$$C_1 = \frac{F_H - K}{F_H - F_L}(S_1 - F_L),$$

$$P_1 = \frac{K - F_L}{F_H - F_L}(F_H - S_1). \tag{A14}$$

Empirically, we find that call volatility increases more than put volatility after a change in the past stock return. Translating this to the model, we can examine

$$\text{cov}(C_2 - C_1 - P_2 + P_1, S_1) = \text{cov}\,(F - S_1, S_1)\,, \tag{A15}$$

where the equality is due to put-call parity, $C_2 - P_2 = (F - K)^+ - (K - F)^+ = F - K$, and we substitute in the price of the call and the put from equation (A14). This is the same as the condition for the predictability of the stock from the past call in equation (A10) and it holds for any strike price.

The expected return of the call option is positive (the call delta is positive) and the expected return of the put option is negative (the put delta is negative). In fact, in this economy, both calls and puts are simple linear securities of the stock. Suppose positive news is released at time 1. Informed traders cause the price of the stock to adjust upward, the price of calls to increase, and the price of puts to decrease. There is still adjustment of the stock price and options from time 1 to time 2, but the stock has already moved toward F_H. This partial adjustment at time 1 causes the next period's adjustment on the put option to be smaller, as the put option delta becomes less negative. A similar intuition works when the news is negative.

Also, note that $(C_2 - C_1) - (P_2 - P_1)$, or equivalently the difference between implied volatilities between calls and puts, is a trading strategy that is long calls and short puts. By put-call parity, this strategy is exposed to the underlying risk of the stock between time 1 and time 2. It is no surprise in our model that the condition for $\mathrm{cov}(C_2 - C_1 - P_2 + P_1, S_1) > 0$ should be equal to $\mathrm{cov}\,(F - S_1, S_1)$, as the conditions under which the long call-short put position is profitable are the same conditions under which the informed trader's signal of a high F is more likely to emerge when S_1 is high.

In this model, the put, call, and stock are linked by no arbitrage, and we cannot observe movements in put and call prices outside the no-arbitrage boundaries. The put and call options are also linear securities. In reality, put and call movements are nonlinear and movements outside arbitrage bounds occur. Extensions to stochastic volatility, along the lines of Back (1993), and American options could be done to accommodate these facts.

Appendix B: 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

$$Var_{i,t}^Q(\tau) = e^{r\tau}V_{i,t}(\tau) - \mu_{i,t}(\tau)^2, \tag{B1}$$

$$Skew_{i,t}^Q(\tau) = \frac{e^{r\tau}W_{i,t}(\tau) - 3\mu_{i,t}(\tau)e^{r\tau}V_{i,t}(\tau) + 2\mu_{i,t}(\tau)^3}{\left[e^{r\tau}V_{i,t}(\tau) - \mu_{i,t}(\tau)^2\right]^{3/2}}. \tag{B2}$$

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

$$V_{i,t}(\tau) = \int_{S_{i,t}}^{\infty} \frac{2(1-\ln(K_i/S_{i,t}))}{K_i^2} C_{i,t}(\tau;K_i)\,dK_i + \int_0^{S_{i,t}} \frac{2(1-\ln(K_i/S_{i,t}))}{K_i^2} P_{i,t}(\tau;K_i)\,dK_i, \tag{B3}$$

$$W_{i,t}(\tau) = \int_{S_{i,t}}^{\infty} \frac{6\ln(K_i/S_{i,t}) - 3[\ln(K_i/S_{i,t})]^2}{K_i^2} C_{i,t}(\tau;K_i)\,dK_i + \int_0^{S_{i,t}} \frac{6\ln(K_i/S_{i,t}) - 3[\ln(K_i/S_{i,t})]^2}{K_i^2} P_{i,t}(\tau;K_i)\,dK_i, \tag{B4}$$

$$X_{i,t}(\tau) = \int_{S_{i,t}}^{\infty} \frac{12[\ln(K_i/S_{i,t})]^2 - 4[\ln(K_i/S_{i,t})]^3}{K_i^2} C_{i,t}(\tau;K_i)\,dK_i + \int_0^{S_{i,t}} \frac{12[\ln(K_i/S_{i,t})]^2 - 4[\ln(K_i/S_{i,t})]^3}{K_i^2} P_{i,t}(\tau;K_i)\,dK_i, \tag{B5}$$

$$\mu_{i,t}(\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}V_{i,t}(\tau)}{2} - \frac{e^{r\tau}W_{i,t}(\tau)}{6} - \frac{e^{r\tau}X_{i,t}(\tau)}{24}, \tag{B6}$$

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 (B1) and (B2) 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

$$Skew_{i,t}^{Q}(\tau) = \beta_i^{3/2}(\tau) Skew_{m,t}^{Q}, \tag{B7}$$

where $Skew_{i,t}^{Q}(\tau)$ and $Skew_{m,t}^{Q}(\tau)$ are estimated using equation (B2). In our empirical analyses, we use volatility surface standardized call and put options with $\tau = 30$ days to maturity to estimate the stock beta from equation (B7). We use volatility surface data on the S&P500 index to compute the risk-neutral market skewness.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix