MANAGEMENT SCIENCE
Vol. 55, No. 11, November 2009, pp. 1797–1812
ISSN 0025-1909 | EISSN 1526-5501 | 09 | 5511 | 1797

DOI 10.1287/mnsc.1090.1063

Volatility Spreads and Expected Stock Returns

Turan G. Bali, Armen Hovakimian
Department of Economics and Finance, Zicklin School of Business, Baruch College, New York, New York 10010
{turan.bali@baruch.cuny.edu, armen.hovakimian@baruch.cuny.edu}

This paper investigates whether realized and implied volatilities of individual stocks can predict the cross-sectional variation in expected returns. Although the levels of volatilities from the physical and risk-neutral distributions cannot predict future returns, there is a significant relation between volatility spreads and expected stock returns. Portfolio level analyses and firm-level cross-sectional regressions indicate a negative and significant relation between expected returns and the realized-implied volatility spread that can be viewed as a proxy for volatility risk. The results also provide evidence for a significantly positive link between expected returns and the call-put options' implied volatility spread that can be considered as a proxy for jump risk. The parameter estimates from the VAR-bivariate-GARCH model indicate significant information flow from individual equity options to individual stocks, implying informed trading in options by investors with private information.

Key words: realized volatility; implied volatility; volatility risk; jump risk; stock returns
History: Received April 16, 2008; accepted June 16, 2009, by David A. Hsieh, finance. Published online in *Articles in Advance* September 11, 2009.

1. Introduction

Bakshi and Kapadia (2003a, b) show the existence of a negative market volatility risk premium in index options and individual equity options, thus providing an explanation of why implied volatilities exceed realized volatilities (Jackwerth and Rubinstein 1996).[1] In this paper, we investigate the cross-sectional pricing of volatility risk in individual stocks by examining whether the realized-implied volatility spread of individual stocks can predict the cross-sectional variation in expected returns.

It has been widely documented that stock returns exhibit both stochastic volatility and jumps, and decomposing the total amount of noise into a continuous Brownian component and a discontinuous jump component has important implications for option pricing, asset allocation, and risk management.[2] Pan (2002) finds a significant premium for jump risk in the S&P 500 index options using the stochastic volatility-jump-diffusion model of Bates (2000).[3] Pan (2002) also provides evidence in support of a jump-risk premium that is highly correlated with the market volatility. Instead of testing the significance of jump-risk premium at the market level, this paper investigates the cross-sectional pricing of jump risk in individual stocks. We find the call-put implied volatility spread to be a proxy for jump risk that has a significantly positive association with expected returns.

We start by examining the relation between "expected future volatility" and the cross-section of expected returns. Earlier studies on the cross-sectional pricing of total or idiosyncratic volatility generally use the past behavior of stock prices to develop expectations about future volatility, modeling movements in volatility as they relate to prior volatility and/or other variables in the investors' information set. Ang et al. (2006, 2009) compute the total variance of an individual stock in month t as the sum of squared daily returns in month $t-1$. In addition to using within-month daily data, Bali and Cakici (2008) use the past 60 months of individual stock returns to generate one-month ahead total volatility. Spiegel and Wang (2005) and Fu (2009) define the conditional volatility of individual stocks as a function of the past residuals and

[1] Adding options to a market portfolio will help hedge market risks as market volatility tends to increase when stock market falls and hence consistent with a negative volatility risk premium.

[2] For instance, in option pricing, the two types of noise have different hedging requirements and possibilities: in optimal portfolio selection, the demand for assets subject to both types of risk can be optimized further if a decomposition of the total risk into a Brownian and a jump part is available; in risk management, such a decomposition makes it possible over short horizons to manage the Brownian risk using Gaussian tools while assessing value-at-risk and other tail statistics based on the identified jump component.

[3] Bates (2000) extends the stochastic volatility model of Heston (1993) by incorporating state-dependent price jumps. Under such a setting, the S&P 500 index returns are affected by three different risk factors: (i) the diffusive price shocks, (ii) the price jumps, and (iii) the diffusive volatility shocks.

the past volatility based on the exponential GARCH model of Nelson (1991). In contrast to these studies, we focus on the market's expectation of future volatility of individual stocks.[4]

We use the reported call and put option prices to infer volatility expectations. The analysis of the returns on portfolios of stocks sorted by call and put implied volatilities over the sample period of January 1996 to December 2004 provides no evidence that expected future volatility (call and put implied volatility) can predict the cross-sectional variation in expected returns during our sample period. In contrast, when we proxy expected volatility with the one-month lagged realized volatility (RVol), as in Ang et al. (2006), we find that portfolios of stocks with low (high) realized volatility earn high (low) average raw and risk-adjusted returns.

As an alternative methodology, we use the Fama-MacBeth (1973) regressions to examine the cross-sectional relation between the three measures of expected volatility and expected returns for individual stocks. None of the three measures (realized, call, and put implied volatility) shows a significant impact on the cross-section of expected returns when it is the only independent variable in the regression. With all three measures on the right-hand side, however, the impacts of the realized and the put implied volatilities are significantly negative, whereas the impact of the call implied volatility is significantly positive. This finding suggests that although the level of volatilities from the physical and risk-neutral distributions cannot predict future returns, there may be a significant relation between *volatility spreads* and the cross-section of expected returns.

Specifically, we examine whether the realized-implied volatility spread (RVol–IVol) and the call-put implied volatility spread (CVol–PVol) can predict the cross-sectional variation in stock returns.[5] A trading strategy that longs stocks in the lowest RVol–IVol quintile and shorts stocks in the highest RVol–IVol quintile produces average raw and risk-adjusted returns in the range of 63 to 73 basis points per month for the value-weighted portfolios and 59 to 63 basis points per month for the equal-weighted portfolios. Portfolio-level analyses and firm-level cross-sectional regressions indicate a negative and significant relation between RVol–IVol and expected returns. A portfolio that longs stocks in the highest CVol–PVol quintile and shorts stocks in the lowest CVol–PVol quintile earns 1.05% to 1.14% per month for the value-weighted portfolios and 1.43% to 1.49% per month for the equal-weighted portfolios. These average raw and risk-adjusted return differences for the RVol–IVol and CVol–PVol portfolios are both economically and statistically significant for the NYSE/AMEX/NASDAQ stocks and the NYSE stocks only.

These results bring us to ask an important question: Is the CVol–PVol spread (proxy for jump risk) priced separately from the RVol–IVol spread (proxy for volatility risk)? An answer to this question has a direct impact on investors' decision making, and could also shed some light on how investors react to various types of uncertainty. According to our bivariate portfolio results, after controlling for the CVol–PVol spread, the average raw and risk-adjusted return differences between the lowest and the highest RVol–IVol quintiles are in the range of 0.50% to 0.60% per month for the value-weighted portfolios and 0.49% to 0.59% per month for the equal-weighted portfolios. Similarly, after controlling for the RVol–IVol spread, the average raw and risk-adjusted return differences between the lowest and the highest CVol–PVol quintiles are in the range of 1.40% to 1.48% per month for the value-weighted portfolios and 1.39% to 1.47% per month for the equal-weighted portfolios. The double sorts on the volatility spreads clearly indicate that jump risk and volatility risk are distinct in the cross-sectional pricing of individual stocks.

These findings remain strong after controlling for the well-known cross-sectional effects identified in the earlier literature, including size and book-to-market (Fama and French 1992, 1993), liquidity and bid-ask spread (Amihud 2002), analyst forecast dispersion (Diether et al. 2002), probability of informed trading (Easley et al. 2002), skewness from the physical distribution (Harvey and Siddique 2000), skewness from the risk-neutral distribution (Xing et al. 2009), and systematic risk proportion (Duan and Wei 2009). The cross-sectional premiums of RVol–IVol and CVol–PVol remain highly significant in both portfolio level analyses and firm-level Fama-MacBeth regressions.

This paper also provides evidence that there is significant volatility spillover effect and information spills over from the options to the stock market. In addition, trading volume of options is found to be informative for the future volume and volatility of underlying stocks. The parameter estimates from the VAR-bivariate-GARCH model indicate significant information flow from individual equity options to individual stocks, implying informed trading in options by investors with private information. The significance of information spillover is stronger in options/stocks with higher volatility spreads.

This paper is organized as follows. Section 2 discusses the data and our sample. Section 3 examines the relation between alternative measures of volatility and the cross-section of expected returns. Section 4 investigates the cross-sectional relation between

[4] Diavatopoulos et al. (2008) introduce a measure of implied idiosyncratic volatility that uses information from both the physical and risk-neutral distributions.

[5] The implied volatility (IVol) of an individual stock is calculated as the average of the call and put implied volatilities.

volatility spreads and expected returns. Section 5 provides a battery of robustness checks after controlling for various well-known cross-sectional effects. Section 6 provides an interpretation for the relation between volatility spreads and expected returns. Section 7 investigates information spillover between individual stocks and options. Section 8 concludes the paper.

2. Data

Our data come from several sources. Financial statement data are from Compustat.[6] Stock return data are from CRSP monthly and daily return files. We retain only data for ordinary common shares (CRSP share codes 10 and 11) and exclude closed-end funds and REITs (SIC codes 6720–6730 and 6798). The factors (Rm-Rf, SMB, and HML) for the three-factor Fama-French (1993) model are downloaded from Kenneth French's online data library.

Option implied volatilities are from the Ivy DB database of OptionMetrics. The Ivy DB database contains daily closing bid and ask prices and implied volatilities for options on individual stocks traded on NYSE, AMEX, and NASDAQ.[7] We retain only stock options with expiration dates in at least 30 days but no more than three months, with positive open interest, positive best bid price, and nonmissing implied volatility. We further delete options with bid-ask spreads exceeding 50% of the average of the bid and ask prices. We focus on near-the-money options with absolute values of the natural log of the ratio of the stock price to the exercise price less than 0.1. We retain the last monthly observation of each option, and then we average the implied volatilities across all eligible options and match with stock returns in the following month. Because options data are available for the period from January 1996 to December 2004 (108 months), we examine monthly stock returns starting in February 1996 and ending in January 2005.

3. Volatility and the Cross-Section of Stock Returns

3.1. Realized Volatility and the Cross-Section of Stock Returns

We start out by replicating in our sample the analysis of the impact of realized volatility (RVol) on stock returns in the cross-section presented by Ang et al. (2006).[8] For each month, we sort all stocks into quintile portfolios based on the realized volatility calculated using daily returns in the previous month.[9] Then the value-weighted returns are calculated for the next month, generating a series of 108 monthly returns. Panel A of Table 1 reports the results for all optionable stocks (i.e., stocks with traded options) with return and volatility data available, a total of 197,362 monthly observations.

The average monthly return, R, of each quintile portfolio is reported in the first column of each panel. The second column reports Jensen's alphas with respect to the Fama-French (1993) three-factor (FF-3) model estimated for each portfolio using 108 monthly returns. The row "5-1" refers to the arbitrage portfolio consisting of a long position in portfolio 5 and a short position in portfolio 1. All returns are reported as percentages. The reported t-statistics are the Newey-West (1987) t-statistics with six lags.

Similar to Ang et al. (2006), the results in panel A show that the average monthly return increases from 0.83% per month to 0.98% per month as we move from quintile 1 (lowest-RVol quintile) to quintile 3. From there, the average returns drop. The average return for the highest-RVol portfolio (quintile 5) is −0.35% per month. The results in the last two rows of panel A show that the average monthly return on "5-1" arbitrage portfolio is economically large (−1.18%), though it is not statistically significant. The FF-3 alpha for the arbitrage portfolio is even larger (−1.58%) and it is highly significant with a t-statistic of −2.4. These numbers are comparable to those in Ang et al. (2006), who report an average monthly return of −1% and the FF-3 alpha of −1.2% for the arbitrage portfolio in their longer sample period (July 1963–December 2000) with all stocks trading at NYSE, AMEX, and NASDAQ. We should note that our sample is much shorter because of data availability at OptionMetrics, and we examine stocks with traded options.

The next three columns present the average values of the realized, call implied, and put implied volatilities for stocks in the RVol quintile portfolios. By construction, average realized volatility increases as we move from quintiles 1 to 5. Not surprisingly, both call and put implied volatilities increase monotonically across the realized volatility quintiles.

The last three columns report the average market share, market capitalization, and book-to-market ratio of stocks in the RVol quintile portfolios. The average market shares of our quintile portfolios are very

[6] To minimize the influence of outliers, financial ratios calculated using Compustat data are trimmed at values representing their 1st and the 99th percentiles.

[7] All the options used in this study are American. OptionMetrics uses the Cox-Ross-Rubinstein binomial tree model (Cox et al. 1979) to calculate the implied volatility of American options.

[8] See panel A of Table VI in Ang et al. (2006, p. 285).

[9] We require each stock to have a minimum of 15 daily return observations when estimating realized volatility.

Table 1 Portfolios Sorted on Realized and Implied Volatilities

Quintile	R, %	Alpha, %	Realized volatility	Call implied volatility	Put implied volatility	Market share	Size	B/M
			Panel A: Realized volatility					
1	0.829	0.010	0.226	0.304	0.310	0.408	9,932	0.540
2	0.940	0.049	0.352	0.401	0.406	0.342	7,360	0.503
3	0.981	0.097	0.498	0.524	0.531	0.160	3,871	0.478
4	0.618	−0.297	0.707	0.659	0.666	0.070	1,978	0.434
5	−0.349	−1.574	1.155	0.789	0.798	0.021	1,016	0.425
5-1	−1.178	−1.584						
t-stat.	−1.0	−2.4						
			Panel B: Call implied volatility					
1	0.565	−0.218	0.266	0.270	0.269	0.456	17,602	0.502
2	1.111	0.234	0.345	0.357	0.362	0.285	11,019	0.502
3	1.181	0.368	0.439	0.455	0.461	0.148	5,837	0.490
4	0.817	0.010	0.580	0.589	0.596	0.078	3,146	0.446
5	0.529	−0.360	0.799	0.806	0.825	0.033	1,354	0.375
5-1	−0.036	−0.142						
t-stat.	0.0	−0.2						
			Panel C: Put implied volatility					
1	0.675	−0.083	0.266	0.261	0.277	0.448	15,449	0.516
2	1.116	0.248	0.346	0.355	0.364	0.286	9,814	0.511
3	1.207	0.384	0.439	0.454	0.462	0.151	5,305	0.501
4	0.683	−0.087	0.578	0.587	0.597	0.080	2,873	0.458
5	0.220	−0.656	0.796	0.816	0.814	0.035	1,257	0.382
5-1	−0.454	−0.573						
t-stat.	−0.3	−0.8						

Notes. Value-weighted quintile portfolios are formed every month by sorting stocks based on realized volatility measured as the standard deviation of daily returns over the previous month (panel A), implied volatility from call (panel B) and put (panel C) prices observed at the end of the previous month. Quintile 1 (5) denotes the portfolio of stocks with the lowest (highest) volatilities. The average monthly returns on quintile portfolios are reported in the column labeled "R." The Jensen's alphas with respect to the Fama-French (1993) three-factor model are reported in the column labeled "Alpha." Market share refers to the average share of the quintile portfolio stocks in the market value of all stocks represented in the table. Size is the average market capitalization and B/M is the average book-to-market ratio for firms within the quintile portfolios. The row "5-1" refers to the average monthly return on an arbitrage portfolio with a long position in portfolio 5 and a short position in portfolio 1. Newey-West (1987) *t*-statistics for the arbitrage portfolio returns are reported in the last row. The sample consists of all NYSE/AMEX/NASDAQ stocks with available data and covers the February 1996–January 2005 period.

similar to those reported in Ang et al. (2006), where they vary between 41% for portfolio 1 and 2.1% for portfolio 5. It is important to note that quintile 5 stocks are much smaller compared to stocks in quintiles 1–4. The book-to-market ratios also decline across the realized volatility quintiles. Overall, the book-to-market ratios are somewhat lower in our sample, likely reflecting the higher valuation multiples of the late 1990s.

To summarize, the results in panel A of Table 1 are quite similar to the results for portfolios sorted on realized volatility reported in Ang et al. (2006). The results confirm the existence of a negative relation between realized volatility and stock returns in our sample, which is much shorter, covers recent years (2001–2004) not covered in the original study, but contains optionable stocks only.

3.2. Implied Volatility and the Cross-Section of Stock Returns

We next repeat the above analysis, but sort stocks into quintile portfolios using volatilities implied by call and put options on the stock. Panels B and C of Table 1 report the results using the call and put implied volatilities, respectively. The overall pattern of average monthly returns across quintile portfolios is similar to the pattern for the realized volatility portfolios in panel A. However, the returns and the FF-3 alphas on arbitrage portfolios formed based on the implied volatility quintiles are statistically indistinguishable from zero.

The finding that arbitrage portfolios based on realized volatility quintiles generate abnormal FF-3 alphas but arbitrage portfolios based on call and put implied volatilities do not, is somewhat puzzling

Table 2 Fama-MacBeth Regressions of Stock Returns on Realized and Implied Volatilities

	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Intercept	0.014	2.7	0.013	1.7	0.017	2.3	0.009	1.7
Realized volatility	−0.011	−0.9					−0.014	−2.3
Call volatility			−0.008	−0.4			0.124	6.4
Put volatility					−0.017	−0.9	−0.101	−6.1

given the monotonically increasing patterns of total and implied volatilities across realized volatility (in panel A, Table 1), call implied volatility (in panel B, Table 1), and put implied volatility (in panel C, Table 1) quintiles.

3.3. Volatility and the Cross-Section of Stock Returns: Fama-MacBeth Regressions

Table 1 presents returns on portfolios formed on the basis of stocks sorted into realized and implied volatility quintiles. An alternative approach is to examine the determinants of individual stock returns using the firm-level cross-sectional Fama-MacBeth (1973) regressions. In Table 2, we report the time-series averages of the slope coefficients from the monthly cross-sectional regressions and their Newey-West adjusted t-statistics generated based on the time-series standard deviation of the coefficient estimates.

Four sets of results are presented. The first three regressions are with the realized, call implied, and put implied volatilities as the only independent variable on the right-hand side. The fourth regression combines all three volatility measures in a single regression. None of the three measures of volatility shows a significant impact on the cross-section of expected returns when it is the only independent variable in the regression. With all three measures on the right-hand side, however, the impacts of the realized and the put implied volatilities are significantly negative, whereas the impact of the call implied volatility is significantly positive.

Specifically, in the last column, the Newey-West t-statistic of the average slope on RVol, CVol, and PVol is −2.3, 6.4, and −6.1, respectively. The results indicate that although the level of volatilities from the physical and risk-neutral distributions cannot predict future returns individually, when we put them together they can significantly predict the cross-sectional variation in expected returns. The differences in the results for realized and implied volatility portfolios as well as individual stock level results from Fama-MacBeth regressions suggest that the impact on future returns may be coming from the orthogonal components of realized and implied volatilities. To examine this question more carefully, we next focus on the relation between volatility spreads and the cross-section of expected returns.

4. Volatility Spreads and the Cross-Section of Stock Returns

4.1. Realized-Implied Volatility Spread

Chernov (2007) and Bollerslev and Zhou (2006) investigate the time-series relation between realized and implied volatilities of the S&P 500 index and find that implied volatilities generally provide upward biased forecasts of future realized volatilities, implying the significance of volatility risk at the market level. Banerjee et al. (2007) find that both the levels and innovations in implied volatility have significant predictive power for future returns on the market portfolio.

Jackwerth and Rubinstein (1996), Coval and Shumway (2001), Bakshi and Kapadia (2003a, b), and Bakshi et al. (2003), using options data, and Bali and Engle (2007), using individual stock data, find a negative market price of volatility risk based on the physical and risk-neutral distributions. The aforementioned studies examine the empirical performance of the level of implied volatility, innovations in implied volatility, and the difference between realized and implied volatility in terms of predicting future realized volatility and predicting future returns on the market portfolio.[10] All of these articles focus on the time-series relation or the market portfolio, or both, whereas we test the presence and significance of a cross-sectional relation between firm-level returns and volatility risk.

For each month t from January 1996 to December 2004, we estimate the realized volatility (RVol) over month t, and we calculate implied volatility (IVol) as the average volatility implied by call and put option prices observed at the end of month t. Once we generate the realized-implied volatility spread RVol–IVol for each stock, we sort all stocks observed in month t into quintile portfolios based on RVol–IVol. This procedure is repeated for each of 108 months in our sample. Specifically, for each quintile portfolio in month t, we examine the return in month $t+1$, generating a series of 108 monthly returns.

Panel A of Table 3 reports the results for NYSE stocks.[11] In addition to calculating value-weighted portfolio returns for the next month, we also compute equal-weighted returns. Furthermore, we report

[10] Andersen et al. (2003) show that innovations in market volatility is proxied by the difference between realized and implied volatility of market returns, because realized volatility is a consistent estimator of actual underlying volatility and implied volatility is an estimator of expected future volatility: innovation in volatility equals actual volatility minus expected volatility.

[11] The results for all NYSE, AMEX, and NASDAQ stocks are similar and can be found in the online supplement, which is provided in the e-companion. An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

alphas with respect to the Fama-French (1993) three-factor model and the abnormal portfolio returns (ARs) calculated relative to characteristic-matched benchmark portfolios. For this, we use 25 benchmark portfolios formed based on the market value of equity (ME) and book-to-market of equity (BM). The breakpoints for the ME and BM portfolio assignments are based on NYSE stock quintile breakpoints and come from Kenneth French's online data library. Stocks are assigned to new ME and BM quintiles each July. Characteristic quintile assignments in year t are based on ME value at the end of June of year t and BM value formed using ME at the end of December of year $t-1$ and book value of equity for the last fiscal year end in year $t-1$.

As shown in panel A of Table 3, for the value-weighted portfolios, we find a negative and economically significant average return difference on RVol–IVol quintile portfolios (in the range of 63 to 73 basis points per month). The average raw, risk-adjusted, and abnormal return differences are all statistically significant as well. For the equal-weighted portfolios, the relation between volatility risk and expected stock returns is also negative and highly significant. A trading strategy buying stocks in the lowest RVol–IVol quintile and shorting stocks in the highest RVol–IVol quintile produces average returns of 59 to 63 basis points per month with the t-statistic of -2.5 to -2.8.

The last three columns of panel A present the average market share, market capitalization, and book-to-market ratio of stocks in the RVol–IVol quintile portfolios. In contrast to the Ang et al. (2006) findings and our findings from the RVol quintiles, the average market share of the highest RVol–IVol quintile is not very small compared to quintiles 1–4. In fact, the average market share of quintile 5 (18.3%) is greater than that of quintile 1 (8.2%). There is not a significant difference between the book-to-market ratios of two extreme quintiles either. The average book-to-market ratio is about 0.60 for the lowest RVol–IVol quintile and 0.55 for the highest RVol–IVol quintile. Overall, the results indicate a negative volatility risk premium of 60 to 73 basis points per month, and as will be discussed later in the paper, this is not attributed to the differences in size and book-to-market characteristics of individual stocks.

4.2. Call-Put Implied Volatility Spread

A high call-put implied volatility spread (CVol–PVol > 0) implies that the call option prices exceed the levels implied by the put option prices and the put-call parity. Ofek et al. (2004) argue that such violations could arise if irrational investors move stock prices (but not options prices) away from their fundamental values and if there are limits to arbitrage, such as short-sale constraints. If this is true, then stocks with relatively more expensive calls (stocks with high CVol–PVol) are expected to generate higher returns than stocks with relatively more expensive puts (stocks with low CVol–PVol). To test our conjecture, we sort all optionable stocks into quintile portfolios based on the spread between call and put implied volatilities in the previous month.

As shown in panel B of Table 3, for both the value-weighted and the equal-weighted portfolios, a long-short portfolio buying stocks in the highest CVol–PVol quintile and shorting stocks in the lowest CVol–PVol quintile produces average returns in the range of 1.00% to 1.49% per month that are highly significant. The t-statistics of average raw, risk-adjusted, and abnormal returns are in the range of 3.9 to 4.5 for the value-weighted portfolios, and range from 7.9 to 8.6 for the equal-weighted portfolios. Because higher CVol–PVol spread indicates that call options are more expensive than put options, higher spread suggests that investors expect the stock price to be higher in the future. In other words, the call-put implied volatility spread reflects expected future price increase of the underlying stock.

Similar to our findings from the RVol–IVol quintiles, this significant call-put volatility premium is not due to the differences in size and book-to-market characteristics of individual stocks. Specifically, the average market shares of quintile 5 (11%) and quintile 1 (13%) are similar. There is not a significant difference between the average book-to-market ratios of the lowest CVol–PVol quintile (0.59) and the highest CVol–PVol quintile (0.56) either.

4.3. Double Sorts on the RVol–IVol and CVol–PVol Spreads

In this section, we test whether the realized-implied volatility spread is priced separately from the call-put implied volatility spread. First, we form quintile portfolios based on the RVol–IVol spread after controlling for the CVol–PVol spread.[12] As shown in panel C of Table 3, the average raw, risk-adjusted, and abnormal return differences between the lowest and the highest RVol–IVol quintiles are in the range of 0.50% to 0.60% per month for the value-weighted portfolios and 0.49% to 0.59% per month for the equal-weighted portfolios. These average return differences are statistically significant, except for the alpha in the value-weighted portfolios. Second, we form quintile portfolios based on the CVol–PVol spread after controlling for the RVol–IVol spread. As reported in the second row of panel C, the average raw, risk-adjusted,

[12] The exact procedure of forming bivariate portfolios is outlined in the next section of the paper.

Table 3 Portfolios Sorted on Realized-Implied Volatility Spread, and Call-Put Implied Volatility Spread

	Value-weighted			Equal-weighted			Characteristics		
Quintile	R, %	AR, %	Alpha, %	R, %	AR, %	Alpha, %	Market share	Size	B/M
	Panel A: Portfolio returns by realized-implied volatility spread (RVol–IVol) quintiles								
1	1.348	0.355	0.276	1.481	0.322	0.069	0.082	3,806	0.597
2	1.227	0.300	0.267	1.279	0.169	−0.029	0.192	8,893	0.540
3	0.847	−0.044	0.000	1.107	−0.002	−0.120	0.268	12,223	0.521
4	0.762	−0.140	−0.050	1.054	−0.055	−0.153	0.275	12,422	0.521
5	0.616	−0.284	−0.356	0.847	−0.254	−0.518	0.183	8,229	0.548
5-1	−0.732	−0.639	−0.632	−0.633	−0.576	−0.587			
t-stat.	−2.9	−2.6	−2.2	−2.8	−2.7	−2.5			
	Panel B: Portfolio returns by call-put implied volatility spread (CVol–PVol) quintiles								
1	0.307	−0.635	−0.727	0.514	−0.598	−0.891	0.107	5,872	0.594
2	0.636	−0.259	−0.310	0.961	−0.104	−0.307	0.219	11,970	0.503
3	0.849	−0.054	0.067	0.927	−0.105	−0.267	0.291	16,076	0.471
4	0.996	0.087	0.148	1.228	0.179	−0.013	0.251	14,050	0.483
5	1.352	0.365	0.413	1.939	0.757	0.596	0.132	7,364	0.556
5-1	1.045	1.000	1.140	1.425	1.355	1.486			
t-stat.	4.2	3.9	4.5	7.9	8.5	8.6			

Panel C: Double-sort RVol–IVol and CVol–PVol portfolios with controls for, respectively, CVol–PVol and RVol–IVol

	Value-weighted						Equal-weighted					
	R, %	*t*-stat.	AR, %	*t*-stat.	Alpha, %	*t*-stat.	R, %	*t*-stat.	AR, %	*t*-stat.	Alpha, %	*t*-stat.
RVol–IVol	−0.599	2.2	−0.493	−1.9	−0.495	−1.8	−0.592	−2.6	−0.528	−2.4	−0.485	−2.0
CVol–PVol	1.402	6.1	1.386	6.4	1.476	6.5	1.391	7.3	1.318	7.9	1.465	8.1

Notes. Each month, all NYSE stocks with available data are sorted into quintile portfolios based on spreads between realized and implied volatilities (RVol–IVol) and between call and put implied volatilities (CVol–PVol), estimated over the previous month. Realized volatility is the standard deviation of daily returns over the previous month. Call (put) volatility is the volatility implied by the call (put) prices at the end of the previous month. Quintile 1 (5) denotes the portfolio of stocks with the lowest (highest) value of the volatility spread. The average monthly returns on quintile portfolios are reported in columns labeled "R." The abnormal returns relative to characteristics-matched benchmark portfolios are reported in columns labeled "AR." We use 25 benchmark portfolios formed based on ME and BM. The Jensen's alphas with respect to the Fama-French (1993) three-factor model are reported in columns labeled "Alpha." Market share refers to the average share of the quintile portfolio stocks in the market value of all stocks represented in the panel. Size is the average market capitalization and B/M is the average book-to-market ratio for firms within the quintile portfolios. The row "5-1" refers to the average monthly return on an arbitrage portfolio with a long position in portfolio 5 and a short position in portfolio 1. Newey-West (1987) *t*-statistics for the arbitrage portfolio returns are reported in the last row. The sample consists of all NYSE stocks with available data and covers the February 1996–January 2005 period.

and abnormal return differences between the lowest and the highest CVol–PVol quintiles are in the range of 1.40% to 1.48% per month for the value-weighted portfolios and 1.39% to 1.47% per month for the equal-weighted portfolios. The double sort on the volatility spreads indicates that RVol–IVol and CVol–PVol spreads are distinct in the cross-sectional pricing of individual stocks.

5. Controlling for Other Cross-Sectional Effects

In this section, we examine whether the significant relations between RVol–IVol and CVol–PVol and returns persist once we control for various cross-sectional effects identified in the earlier literature as factors with significant impact on returns. Unlike in earlier tests, we form volatility spread quintile portfolios while controlling for one other characteristic at a time. All of the following results are for the sample that consists of the NYSE stocks only.

Our procedure follows Ang et al. (2006). Specifically, each month, the stocks are first sorted into quintiles based on the control characteristic (e.g., size). Then, within each characteristic quintile, the stocks are sorted based on RVol–IVol (panel A of Table 4) or CVol–PVol (panel B of Table 4). Each characteristic quintile, thus, contains five volatility-spread quintiles. Next, volatility spread quintiles 1 from each control characteristic quintile are averaged into a single quintile 1, volatility spread quintiles 2 are averaged into a single quintile 2, etc. The resulting volatility spread quintiles contain stocks with all values of the characteristic and, hence, represent volatility spread quintile portfolios controlling for the characteristic. In Table 4, we report the raw returns, ARs, and FF-3 alphas of the "5-1" arbitrage portfolios formed on the basis of these quintiles.

Table 4 Volatility Spread Arbitrage Portfolios with Controls for Other Cross-Sectional Effects

	Value-weighted						Equal-weighted					
	R, %	*t*-stat.	AR, %	*t*-stat.	Alpha, %	*t*-stat.	R, %	*t*-stat.	AR, %	*t*-stat.	Alpha, %	*t*-stat.
						Panel A: RVol–IVol						
Size	−0.628	−2.7	−0.579	−2.5	−0.625	−2.3	−0.679	−3.0	−0.620	−2.8	−0.674	−2.6
Book-to-market	−0.794	−3.8	−0.789	−4.0	−0.778	−3.5	−0.601	−2.8	−0.605	−2.8	−0.557	−2.5
Illiquidity	−0.755	−3.4	−0.677	−3.3	−0.735	−3.3	−0.585	−2.7	−0.488	−2.3	−0.576	−2.3
Bid-ask	−0.904	−3.0	−0.859	−2.9	−0.830	−2.5	−0.500	−2.4	−0.464	−2.1	−0.536	−2.3
AFD	−0.647	−2.6	−0.525	−2.5	−0.564	−2.3	−0.607	−2.7	−0.557	−2.6	−0.540	−2.4
PIN	−0.478	−1.5	−0.437	−1.5	−0.333	−1.1	−0.756	−3.1	−0.689	−2.9	−0.727	−2.8
Skewness	−0.750	−3.3	−0.624	−2.8	−0.523	−1.8	−0.688	−3.3	−0.634	−3.1	−0.609	−2.7
Q-skew	−0.321	−0.8	−0.202	−0.5	−0.284	−0.7	−0.668	−2.3	−0.593	−2.1	−0.569	−1.6
SRP	−0.684	−3.0	−0.547	−2.3	−0.644	−2.5	−0.623	−2.8	−0.581	−2.6	−0.619	−2.6
						Panel B: CVol–PVol						
Size	1.458	6.9	1.455	7.0	1.549	7.8	1.483	6.6	1.475	7.1	1.547	7.3
Book-to-market	0.987	3.8	1.011	4.1	1.044	4.2	1.401	7.5	1.322	7.7	1.445	9.0
Illiquidity	1.482	7.1	1.464	7.3	1.556	7.2	1.415	6.7	1.394	7.2	1.486	7.2
Bid-ask	1.355	4.4	1.294	4.4	1.434	4.7	1.476	6.4	1.449	7.0	1.559	7.0
AFD	1.425	5.4	1.388	5.8	1.491	5.6	1.482	7.9	1.406	8.1	1.540	9.0
PIN	1.537	6.5	1.418	6.9	1.556	6.0	1.683	8.3	1.591	8.5	1.698	8.9
Skewness	1.132	5.1	1.083	5.1	1.227	5.2	1.361	8.1	1.282	8.5	1.400	8.8
Q-skew	0.587	1.6	0.512	1.6	0.833	2.2	0.776	2.6	0.711	2.5	0.871	3.1
SRP	1.026	5.4	0.967	5.2	1.085	5.0	1.424	8.4	1.378	9.3	1.484	9.1

Notes. Each month, all NYSE stocks with available data are first sorted based on firm characteristic (size, illiquidity, bid-ask spread, AFD, PIN, skewness, *Q*-skew, and SRP) and then, within each characteristic quintile the stocks are sorted based on the RVol–IVol (panel A) or CVol–PVol (panel B). Realized volatility (RVol) is the standard deviation of daily returns over the previous month. Call (CVol) and put (PVol) volatilities are the volatilities implied by, respectively, the call and put prices at the end of the previous month. Implied volatility (IVol) is the volatility implied by both call and put prices at the end of the previous month. The five RVol–IVol (CVol–PVol) quintile portfolios are then averaged over each of the five characteristic portfolios. Hence, they represent RVol–IVol (CVol–PVol) quintile portfolios controlling for the characteristic. Each row reports the average monthly returns on an arbitrage portfolio with a long position in quintile portfolio 5 and a short position in quintile portfolio 1, controlling for the characteristic. The average monthly raw returns on the portfolios are reported in columns labeled "R." The abnormal returns relative to characteristics-matched benchmark portfolios are reported in columns labeled "AR." We use 25 benchmark portfolios formed based on ME and BM. The Jensen's alphas with respect to the Fama-French (1993) three-factor model are reported in columns labeled "Alpha." Size is the market capitalization of the stock. Illiquidity is Amihud's (2002) measure of illiquidity. Bid-ask is the percentage bid-ask spread relative to the average of the bid and the ask prices. AFD is the analyst forecast dispersion measured as the standard deviation of analyst forecasts scaled by mean analyst forecast. PIN is the probability of information-based trading. Skewness is the skewness of the daily returns over the previous month. *Q*-skew is the risk-neutral measure of skewness of stock returns. SRP is the systematic risk proportion, defined as the ratio of systematic variance to total variance of individual stock returns. The reported *t*-statistics are Newey-West (1987) adjusted. The sample consists of all NYSE stocks with available data and covers the February 1996–January 2005 period.

5.1. Controlling for Size and Book-to-Market

Although the characteristic-matched ARs and the FF-3 alphas incorporate controls for size and book-to-market, we perform additional controls using the above-described procedure. The first line in each panel represents the arbitrage portfolio returns when volatility spread portfolios are formed controlling for size. Both for RVol–IVol and CVol–PVol, the returns, ARs, and FF-3 alphas of both the equal-weighted and value-weighted arbitrage portfolios remain economically large and statistically significant. These results imply that size explains neither of the two volatility-spread effects.

The second line in each panel represents the arbitrage portfolio returns when RVol–IVol and CVol–PVol portfolios are formed controlling for book-to-market. Both for RVol–IVol and CVol–PVol, the returns, ARs, and FF-3 alphas of both the equal-weighted and the value-weighted arbitrage portfolios remain economically large and statistically significant, implying that variations in the book-to-market ratio are not responsible for the observed RVol–IVol and CVol–PVol effects.

5.2. Controlling for Illiquidity

We next use Amihud's (2002) illiquidity measure as a control variable.[13] Amihud finds that illiquid stocks earn higher returns. The bivariate portfolio results, reported in the third rows of panels A (RVol–IVol) and B (CVol–PVol), show that the significant returns on RVol–IVol and CVol–PVol arbitrage portfolios are robust to controlling for illiquidity. Depending on the type of risk control and the portfolio weighting scheme, the average arbitrage portfolio returns vary

[13] This measure of illiquidity is calculated as the ratio of the daily absolute stock return to its daily dollar volume, averaged over the previous month.

between −0.5% and −0.8% per month for RVol–IVol, and between 1.4% and 1.5% per month for CVol–PVol. All the returns are statistically significant.

5.3. Controlling for Bid-Ask Spread

Another way to control for liquidity is to use the bid-ask spread. For each stock and each month, we calculate the mean daily percentage bid-ask spread over the previous month. The percentage bid-ask spread is the difference between ask and bid prices scaled by the mean of the bid and ask prices. The arbitrage portfolio returns controlling for bid-ask spread are presented in the fourth rows of panels A and B. The returns remain economically large and statistically significant. FF-3 alphas for the RVol–IVol arbitrage portfolios are –0.5% with equal weighting and –0.9% with value weighting. FF-3 alphas for the CVol–PVol arbitrage portfolios are 1.4% per month for the value weighted portfolio and 1.6% per month for the equal-weighted portfolio.

5.4. Controlling for Analyst Forecast Dispersion

The analyst forecast dispersion (AFD) is calculated as the standard deviation of the analysts' forecasts of the next fiscal year's earnings per share scaled by the mean analyst forecast.[14] Diether et al. (2002) show that higher dispersion in analysts' earnings forecasts, which they argue proxies for the differences in investors' opinions, is associated with lower subsequent average returns. According to Miller (1977), in the presence of short sale constraints, the views of the more pessimistic investors will tend not to be reflected in stock prices, leading such stocks to be overpriced and reducing their future expected returns.

The results controlling for AFD are presented in the fifth rows of panels A and B. The returns, ARs, and FF-3 alphas of all arbitrage portfolios remain statistically and economically significant. The RVol–IVol based FF-3 alphas, for example, are −0.6% for the value-weighted portfolio and −0.5% for the equal-weighted portfolio. The CVol–PVol based FF-3 alphas are about 1.5% for both the value-weighted and the equal-weighted portfolios.

5.5. Controlling for Informed Trading

Easley and O'Hara (2004) present a model showing that private information-based trading affects the cross-section of expected returns. Easley et al. (2002) generate a measure of the probability of information-based trading (PIN) and show empirically that stocks with higher probability of information-based trading have higher returns.

[14] These variables come from the Institutional Brokers' Estimate System (IBES) summary of estimates file.

Using the PIN as a control variable, we investigate whether the predictability from RVol–IVol and CVol–PVol is driven by their correlation with concentration of informed traders.[15] These results are reported in the sixth rows of panels A and B of Table 4. Controlling for PIN does affect the returns of the value-weighted RVol–IVol arbitrage portfolios. Value weighted portfolio returns decline in magnitude and become insignificant at the 5% level. The equal-weighted arbitrage portfolio returns, however, remain significant. The equal-weighted FF-3 alpha is −0.7% per month, which is similar to our earlier findings from the univariate portfolios. Controlling for PIN does not affect the returns on CVol-PVol arbitrage portfolios. The returns, ARs, and FF-3 alphas, all remain large and significant.

5.6. Controlling for Skewness from the Physical Distribution

Harvey and Siddique (2000) show that coskewness with the market has a significant impact on expected returns. Barberis and Huang (2008) demonstrate that investors with prospect theory based utility functions prefer idiosyncratic skewness, which affects equilibrium expected returns.

The results controlling for skewness are presented in the seventh rows of panels A and B of Table 4.[16] Although controlling for skewness does not affect the arbitrage returns and ARs of RVol–IVol portfolios, the FF-3 alpha of the value-weighted arbitrage portfolio becomes marginally significant with the t-statistic equal to −1.8. For CVol–PVol portfolios, controlling for skewness does not affect our original findings. The returns, ARs, and FF-3 alphas, all remain large and significant. For example, the FF-3 alphas are 1.2% for the value-weighted portfolio and 1.4% for the equal-weighted portfolio, and both alphas are highly significant.

5.7. Controlling for Skewness from the Risk-Neutral Distribution

We next control for a risk-neutral measure of skewness, Q-skew, when forming volatility spread quintile portfolios. Xing et al. (2009) define the risk-neutral or Q measure of skewness (which is also called "volatility smirk") as the difference between the

[15] We downloaded NYSE stock PIN values from Soeren Hvidkjaer's website, http://www.smith.umd.edu/faculty/hvidkjaer/data.htm (accessed December 29, 2006; site now discontinued). The data are annual and are available through 2001. Because we use the PIN in year (t) to predict monthly returns in year ($t+1$), the sample used in this analysis starts in February 1996 and ends in December 2002 for a total of 83 months.

[16] We calculate skewness from daily return observations over the previous month. Minimum 15 daily return observations are required.

out-of-the-money put and at-the-money call implied volatilities.[17,18]

In Table 4, Q-skew equals out-of-the-money put implied volatility minus at-the-money call implied volatility. Earlier in the paper, we used call and put implied volatilities of at-the-money options defined as options with absolute values of the natural log of the ratio of the stock price to the exercise price less than 0.1. Here, we use the same definition for at-the-money call, with the put option defined as out-of-the-money when natural log of the ratio of the stock price to the exercise price is more than 0.1.

As shown in Table 4, for the equal-weighted portfolios, the average raw, abnormal, and risk-adjusted return differences between the high CVol–PVol and low CVol–PVol portfolios remain positive and significant after controlling for Q-skew. For the value-weighted portfolios, the difference in FF-3 alphas is positive and significant, and the average raw and abnormal return differences remain to be positive, economically significant (0.51% to 0.59% per month), but they are not statistically significant. Similarly, for the equal-weighted portfolios, the average return differences between the high and low RVol–IVol quintiles remain negative and significant after controlling for Q-skew. For the value-weighted portfolios, the average return differences turn out to be negative, but statistically insignificant. These results suggest that the information content of the realized-implied volatility spread is somewhat related to the information content of Q-skew for the large optionable stocks.

5.8. Controlling for Systematic Risk Proportion

Duan and Wei (2009) show that the level of implied volatility and the slope of implied volatility curve is a function of moneyness, risk-neutral skewness, and risk-neutral kurtosis. All of them are functions of systematic risk proportion (SRP).[19]

Based on the one-factor CAPM equation, $R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$, we can write total variance (σ_i^2) as the sum of systematic variance ($\beta_i^2\sigma_m^2$) and idiosyncratic variance (σ_ε^2): $\sigma_i^2 = \beta_i^2\sigma_m^2 + \sigma_\varepsilon^2$. Following Duan and Wei (2009), we define *systematic risk proportion* as the ratio of systematic variance to total variance of individual stock returns: $\beta_i^2\sigma_m^2/\sigma_i^2$. Note that this measure is not the absolute amount of market beta; rather, it is the relative proportion. Following Duan and Wei (2009), we use daily returns over the past one year to run the one-factor CAPM and estimate SRP.[20]

As shown in Table 4, the significantly negative relation between RVol–IVol and expected returns and the significantly positive relation between CVol–PVol and expected returns remain intact after controlling for SRP of individual stocks.

5.9. Fama-MacBeth Regressions

An alternative approach to controlling for various determinants of cross-sectional variation in stock returns is to run Fama-MacBeth (1973) regressions of returns on these determinants. We compute the time-series averages of the slope coefficients from the monthly cross-sectional regressions and their Newey-West adjusted t-statistics. Consistent with our earlier results presented in panel C of Table 3, when RVol–IVol and CVol–PVol are the only independent variables in the regression, the effect of RVol–IVol is significantly negative, and the effect of CVol–PVol is significantly positive. Although not reported in the paper to save space, the average slope on RVol–IVol is found to be −0.016 with the t-statistic of −2.5 and the average slope on CVol–PVol is found to be 0.107 with the t-statistic of 5.9. When we control for size, book-to-market, illiquidity, AFD, PIN, skewness from the physical and risk-neutral distributions, and SRP, the effects of RVol–IVol and CVol–PVol on expected returns remain statistically significant: the average slope on RVol–IVol is about −0.020 with the t-statistic equal to −2.6 and the average slope on CVol–PVol is about 0.131 with the t-statistic equal to 2.6.

6. Interpretation of Volatility Spreads

6.1. Interpretation of the Realized-Implied Volatility Spread

Assume that an individual stock price process follows a one-factor market model:

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \varepsilon_{i,t}, \tag{1}$$

where return on stock i, $R_{i,t}$, has a market component, $R_{m,t}$, and an idiosyncratic component, $\varepsilon_{i,t}$. Taking the

[17] Higher volatility smirks in individual options should reflect higher probabilities of large negative price jumps. Hence, firms with higher Q-skew should have lower subsequent returns compared to firms with lower Q-skew. Consistent with this prediction, Xing et al. (2009) find that stocks with higher volatility smirk (or Q measure of skew) generate lower returns than stocks with lower volatility smirk.

[18] As shown in the online supplement, the average raw and risk-adjusted return differences between high Q-skew and low Q-skew portfolios are found to be negative in our sample, 0.8% to 1.2% per month and highly significant, confirming the findings of Xing et al. (2009).

[19] Duan and Wei (2009) examine the relation between SRP and the prices of individual equity options. They find that after controlling for total risk, a higher level of systematic risk leads to a higher level of implied volatility and a steeper of the implied volatility curve. Hence, they conclude that SRP can help explain the cross-sectional variation in individual equity options. Duan and Wei (2009) do not examine the impact of SRP on the cross-sectional variation in individual stock returns.

[20] The minimum number of trading days we require for this estimation is 100 over the past one year.

variance of both sides of Equation (1) gives $\sigma_i^2 = \beta_i^2\sigma_m^2 + \sigma_{\varepsilon,i}^2$. Following Bakshi and Kapadia (2003b) and Duan and Wei (2009), we assume idiosyncratic risk is diversified away, which yields $\sigma_i^2 = \beta_i^2\sigma_m^2$.

Based on the theoretical evidence provided by Bakshi et al. (2003), Duan and Wei (2009) show that for the physical and risk-neutral return distributions, the realized and implied volatility of an individual stock i ($\mathrm{RVol}_i, \mathrm{IVol}_i$) must have some exposure to the realized and implied volatility of the market portfolio ($\mathrm{RVol}_m, \mathrm{IVol}_m$) through the market beta of the stock i; i.e., $\mathrm{RVol}_i = \beta_i \cdot \mathrm{RVol}_m$ and $\mathrm{IVol}_i = \beta_i \cdot \mathrm{IVol}_m$. This leads the realized-implied volatility spread of stock i ($\mathrm{RVol}_i - \mathrm{IVol}_i$) to be a positive function of the realized-implied volatility spread of the market portfolio ($\mathrm{RVol}_m - \mathrm{IVol}_n$):

$$\mathrm{RVol}_i - \mathrm{IVol}_i = \beta_i \cdot (\mathrm{RVol}_m - \mathrm{IVol}_m). \tag{2}$$

A large number of studies (e.g., Jackwerth and Rubinstein 1996; Bakshi and Kapadia 2003a, b; Bollerslev and Zhou 2006; Chernov 2007; Banerjee et al. 2007) find the market volatility risk premium to be negative. Because the market beta in Equation (2) is positive ($\beta_i > 0$), the realized-implied volatility spread of an individual stock ($\mathrm{RVol}_i - \mathrm{IVol}_i$) is expected to have a negative risk premium as well.

Following earlier studies (e.g., Bakshi and Kapadia 2003a, b; Duan and Wei 2009), in Equation (2), the market beta from the physical and risk-neutral return distributions are assumed to be the same. However, this may not be true empirically because of different natures of stochastic volatility and higher-order moments in the physical and risk-neutral distributions. In this section, we test this hypothesis by running the following the regressions:

$$\mathrm{RVol}_{i,t} = \alpha_i^P + \beta_i^P \cdot \mathrm{RVol}_{m,t} + \varepsilon_{i,t}^P, \tag{3}$$

$$\mathrm{IVol}_{i,t} = \alpha_i^Q + \beta_i^Q \cdot \mathrm{IVol}_{m,t} + \varepsilon_{i,t}^Q, \tag{4}$$

$$\mathrm{RVol}_{i,t} - \mathrm{IVol}_{i,t} = a_i + b_i \cdot (\mathrm{RVol}_{m,t} - \mathrm{IVol}_{m,t}) + u_{i,t}. \tag{5}$$

For each stock in our sample, we first estimate Equation (3) by using the monthly realized volatility of individual stocks and the monthly realized volatility of the market portfolio (proxied by the S&P 500 index). Regressing $\mathrm{RVol}_{i,t}$ on $\mathrm{RVol}_{m,t}$ yields an average β_i^P of 1.3593 and a median value of 1.1450. Second, we estimate Equation (4) based on the monthly implied volatility of individual stocks and the monthly implied volatility of the market, proxied by the S&P 500 implied volatility index (known as the VIX) available at the Chicago Board Options Exchange. Regressing $\mathrm{IVol}_{i,t}$ on $\mathrm{IVol}_{m,t}$ gives an average β_i^Q of 0.8651 and a median value of 0.7736. Finally, we estimate Equation (5) by regressing the realized-implied volatility spread of individual stocks ($\mathrm{RVol}_i - \mathrm{IVol}_i$) on the realized-implied volatility spread of the market ($\mathrm{RVol}_m - \mathrm{IVol}_m$), which gives an average slope of $b_i = 0.8469$ and a median slope of $b_i = 0.6846$.

A notable point is that the volatility beta estimates (β_i^P, β_i^Q, b_i) of individual stocks, which can be viewed as the loadings to the realized market volatility risk, are on average positive. Another notable point is that both the average and the median values of β_i^P, β_i^Q, b_i are statistically significant at the 1% level. These results indicate that volatility risk of individual stocks has a significantly positive loading to the market volatility risk, ($\mathrm{RVol}_m - \mathrm{IVol}_m$), which has a negative premium as shown by the aforementioned studies.

Previous work finds negative market volatility risk premium in index options, individual equity options, and equity indices. The parameter estimates from Equation (5) show that the realized-implied volatility spread of an individual stock has a positive exposure to the realized-implied volatility spread of the market. The significantly positive loadings to ($\mathrm{RVol}_m - \mathrm{IVol}_m$) and the negative market volatility risk premium together provide supporting evidence for the existence of a negative volatility risk premium for individual stocks.[21]

6.2. Interpretation of the Call-Put Implied Volatility Spread

Recent papers have addressed the importance of distinguishing between jumps and continuous sample path price movements: (i) the parametric models of Eraker et al. (2003) and Chernov et al. (2003); (ii) the Markovian, nonparametric analysis of Ait-Sahalia (2004), Ait-Sahalia and Jacod (2009), and Johannes (2004); (iii) the options-based approach of Bates (1996); and (iv) the quadratic bipower variation approach of Barndorff-Nielsen and Shephard (2004, 2006).

Based on Merton (1976) and many other follow-up studies, we assume the following stock price process:

$$dS_t/S_t = \mu_t dt + \sigma_t dW_t + (\exp(J_t) - 1) dZ_t, \tag{6}$$

where μ_t is the drift, σ_t is the diffusion volatility when there is no random jump, W_t is a standard Wiener process, Z_t is a counting process with finite intensity λ_t ($0 \le \lambda_t < \infty$), and J_t is random jump return with mean μ_J. By applying Ito's lemma to Equation (6), we obtain the difference between the instantaneous simple return (dS_t/S_t) and log return ($d \ln S_t$):

$$2\int_0^1 (dS_t/S_t - d\ln S_t) = \int_0^1 \sigma_t^2\, dt + 2\int_0^1 (\exp(J_t) - J_t - 1)\, dZ_t. \tag{7}$$

[21] We thank the referee for pointing out this line of research.

Suppose that stock prices are observed at time interval of Δ with n observations of log returns over the time period $[0, 1]$, i.e., $\Delta = 1/n$: $\{r_{\Delta i} = \ln(S_{\Delta i}/S_{\Delta(i-1)})\}_{i=1,\ldots,n}$. As shown by Andersen et al. (2003), the realized variance measure, $RV = \sum_{i=1}^{n} r_{\Delta i}^2$, is a consistent estimator of integrated return variance. In addition, a discretized version of the variance swap measure can also be constructed as $SV = 2\sum_{i=1}^{n}(R_{\Delta i} - r_{\Delta i})$, where the simple return of the stock is $R_{\Delta i} = (S_{\Delta i} - S_{\Delta(i-1)})/S_{\Delta(i-1)}$.

Based on Equations (6) and (7) and the quadratic bipower variation approach of Barndorff-Nielsen and Shephard (2004, 2006), Jiang and Oomen (2008) define the *jump return* over the period of n observations as $JR = (RV - BP)^2/(3(SV - RV))$, where $BP = (\pi/2)\sum_{i=1}^{n-1} |r_{\Delta,\, i+1}| \cdot |r_{\Delta,\, i}|$. We should note that Jiang and Oomen (2008) decompose total return into diffusion and jump components. We are particularly interested in total volatility (or total risk) of the jump component.

To test whether the call-put implied volatility spread is a proxy for "jump risk," we first generate daily returns on each quintile portfolio of CVol–PVol. Then, using the approach of Barndorff-Nielsen and Shephard (2004, 2006) and Jiang and Oomen (2008), we compute cumulative one-year jump returns based on the daily returns of CVol–PVol quintile portfolios. Finally, we calculate the standard deviation of jump returns of CVol–PVol portfolios. As reported in the first column of the Table 5, the jump risk of the highest CVol–PVol quintile is greater than the jump risk of the lowest CVol–PVol quintile. Specifically, for the portfolio returns of optionable stocks, total risk of jump returns is 11.78% per annum for the lowest CVol–PVol quintile and 37.94% per annum for the highest CVol–PVol quintile. Also, jump risk increases almost monotonically when moving from quintiles 1 to 5.

In addition to examining the jump risk of portfolio returns, we generate cumulative one-year jump returns for each stock in our sample. The second column of Table 5 reports the average standard deviation of jump returns of optionable stocks within each quintile. Although there is not a monotonic increase from quintiles 1 to 5, the average jump risk of optionable stocks in quintile 5 (13.80% per annum) is significantly greater than the average jump risk of optionable stocks in quintile 1 (8.00% per annum). Overall, these results indicate that stocks with higher call-put implied volatility spread have higher jump risk.[22]

Table 5 Jump Risk by Call-Put Implied Volatility Spread Quintiles

Quintile	Jump risk of CVol–PVol portfolio returns (%)	Average jump risk of individual stock returns (%)
1	11.78	8.00
2	10.43	15.36
3	16.01	14.84
4	15.53	18.19
5	37.94	13.80

7. Information Spillover

As an alternative to the "irrational investors" argument of Ofek et al. (2004), we also examine whether the option prices can predict the future direction of the stock prices because investors trading options are better informed about the value of the underlying asset than those trading the underlying asset. Specifically, we test whether the option prices forecast the future stock price movement by introducing an econometric model that demonstrates the interaction between stock and option traders, and how individual equity options leads individual stocks. We expect to find evidence that there is significant information in options that has not been incorporated in individual stocks.

We investigate the significance of information spillover between individual stocks and stock options using the following vector autoregressive (VAR) bivariate generalized autoregressive conditional heteroskedasticity (GARCH) framework:

$$R_{1,\,t} = \alpha_0 + \alpha_1 \cdot R_{1,\,t-1} + \alpha_2 \cdot R_{2,\,t-1} + \varepsilon_{1,\,t}, \tag{8}$$

$$R_{2,\,t} = \beta_0 + \beta_1 \cdot R_{2,\,t-1} + \beta_2 \cdot R_{1,\,t-1} + \varepsilon_{2,\,t}, \tag{9}$$

$$E(\varepsilon_{1,\,t}^2 \mid \Omega_{t-1}) = \sigma_{1,\,t}^2 = \gamma_0 + \gamma_1 \varepsilon_{1,\,t-1}^2 + \gamma_2 \sigma_{1,\,t-1}^2 + \gamma_3 \varepsilon_{2,\,t-1}^2 + \gamma_4 \sigma_{2,\,t-1}^2, \tag{10}$$

$$E(\varepsilon_{2,\,t}^2 \mid \Omega_{t-1}) = \sigma_{2,\,t}^2 = \delta_0 + \delta_1 \varepsilon_{2,\,t-1}^2 + \delta_2 \sigma_{2,\,t-1}^2 + \delta_3 \varepsilon_{1,\,t-1}^2 + \delta_4 \sigma_{1,\,t-1}^2, \tag{11}$$

$$E(\varepsilon_{1,\,t}\varepsilon_{2,\,t} \mid \Omega_{t-1}) = \sigma_{12,\,t} = \theta_0 + \theta_1 \varepsilon_{1,\,t-1}\varepsilon_{2,\,t-1} + \theta_2 \sigma_{12,\,t-1}, \tag{12}$$

where $R_{1,\,t}$ denotes daily return on an individual stock, and $R_{2,\,t}$ denotes daily return on the call, put, and straddle written on the individual stock. As shown in Equations (8) and (9), the conditional mean of daily returns on the stock and the stock option is modeled as a VAR of order one process. As presented in Equations (10) and (11), the current conditional variance of daily returns on the stock and the option ($\sigma_{1,\,t}^2$, $\sigma_{2,\,t}^2$) is parameterized as a function of the last period's unexpected information shocks to the stock ($\varepsilon_{1,\,t-1}$) and the option ($\varepsilon_{2,\,t-1}$) as well as the last period's variance of the stock ($\sigma_{1,\,t-1}^2$) and the

[22] We thank the referee for pointing out this line of research, which led to a considerable improvement of our paper.

option ($\sigma^2_{2,t-1}$). In Equation (12), the current conditional covariance ($\sigma_{12,t}$) is parameterized as a function of the product of the residuals ($\varepsilon_{1,t-1}\varepsilon_{2,t-1}$) and the last period's covariance ($\sigma_{12,t-1}$).

The VAR-bivariate-GARCH model in Equations (8)–(12) enables an investigation of lead-lag relationships, or information spillover effects, in both the conditional mean and conditional variance equations. The parameters are estimated using the maximum likelihood methodology based on the daily returns on individual stocks and stock options for the sample period of January 1996 to December 2004. We use near-the-money call and put option prices to generate option returns. We choose the call and put options with closer to one month to maturity and with the highest trading volume. We first form portfolios based on the RVol–IVol and CVol–PVol spreads, and then test the significance of information spillover across the quintiles. Our objective is to test whether the information spillover is strongest in stocks and options placed in the higher volatility spread quintiles. Once the entire set of parameters in Equations (8)–(12) are estimated for each stock and option using daily data, we report in Table 6 the average values and *t*-statistics of the spillover parameters ($\gamma_3, \gamma_4, \delta_3, \delta_4$) in the conditional variance equations because the spillover parameters in the conditional mean turn out to be statistically insignificant.

Information spillover effects are examined in an information asymmetry context. Cherian and Jarrow (1998) and Nandi (1999) indicate that informed investors who know the direction of the change in price of certain stocks, which uninformed investors do not know, are likely to trade in the stock market. In contrast, informed investors who only know that the stock prices will change, but not whether the prices will increase or decrease, are likely to trade in the options market.[23] The VAR-bivariate-GARCH model provides a framework for investigating whether directional and unidirectional information are independent or if one type of information precedes the other. Cox and Rubinstein (1985) state that directional and unidirectional information might indeed simultaneously exist independently of each other. Intuitively, it is reasonable to assume that unidirectional information leads directional information, as it is more general. The two types of information are defined as shocks to the stock and option price process. Thereby, it is possible to test informational lead-lag relationships between individual stocks and options, taking into account spillover effects in the first moment (conditional mean) and the second moment (conditional variance).

Although not presented in the paper to save space, the maximum likelihood parameter estimates of the VAR-bivariate-GARCH model provides no evidence for significant autocorrelations and cross-correlations in the conditional mean. Specifically, the parameters (α_2, β_2) in Equations (8) and (9) are estimated to be statistically insignificant (or marginally significant in some cases) for stocks/options in the RVol–IVol and CVol–PVol quintiles, indicating no information spillover effects between the conditional means of stock and options returns or vice versa.

As reported in Table 6, significant information spillover effects between stocks and stock options are detected in the conditional variance equation. Specifically, lagged squared shocks to the stock and option price process do affect the conditional stock return variance because the parameters (γ_3, γ_4) are found to be statistically significant in most quintiles except for the lowest RVol–IVol and CVol–PVol quintiles. That is, today's call return shocks, put return shocks, and straddle return shocks as well as today's option return variances have an effect on tomorrow's conditional variance of stock returns. The degree of statistical significance is generally greater in the higher RVol–IVol and CVol–PVol quintiles, suggesting that the significance of information spillover is stronger for options/stocks with higher volatility spreads.

However, the conditional variance of options returns is only affected by the lagged squared options return shocks and the lagged variance of options returns because the parameters (δ_3, δ_4) are generally statistically insignificant,[24] implying that today's stock return shocks and stock return variance do not have much influence on the conditional variance of options returns.[25]

These results are consistent with the idea that new unidirectional information (represented by options return shocks) precedes directional information (represented by stock return shocks), or that information spills over from individual equity options to individual stocks, implying informed trading in options by investors with private information. The volatility spillover effect implies that the options market generally leads the stock market or information from the

[23] Consistent with the sequential trade model of Easley et al. (1998), Cremers and Weinbaum (2009) find evidence suggesting that informed investors choose to trade in options before trading in the underlying stocks.

[24] There are only a very few exceptions in the lowest RVol–IVol quintile and the quintiles 1 and 5 of CVol–PVol spread that stock return shocks or stock return variances or both, can have an influence on the conditional variance of options returns.

[25] Many studies suggest that price movements in the futures markets systematically lead price movements of the underlying index in the cash markets (see, e.g., Kawaller et al. 1987, Stoll and Whaley 1990, Chan et al. 1991). Berndt and Ostrovnaya (2007) find a significant information flow from both credit and option markets to equity markets in the days leading up to adverse credit or option market events.

Table 6 Information Spillover from Individual Equity Options to Individual Stocks

	Quintile 1			Quintile 2			Quintile 3			Quintile 4			Quintile 5		
	Call	Put	Straddle	Call	Put	Straddle	Call	Put	Straddle	Call	Put	Straddle	Call	Put	Straddle
Panel A: Individual stocks/options in RVol–IVol portfolios															
γ_3	−0.0870	−0.0440	−0.0359	−0.0923	−0.1472	−0.1100	−0.1003	−0.1544	−0.1203	−0.1357	−0.1828	−0.1571	−0.1596	−0.1827	−0.1698
	(−0.89)	(−0.29)	(−1.43)	(−1.69)	(−1.88)	(−1.90)	(−1.87)	(−1.97)	(−2.01)	(−2.05)	(−2.18)	(−2.34)	(−2.14)	(−2.95)	(−3.21)
γ_4	0.0755	0.0832	0.0282	0.1120	0.1532	0.0739	0.1650	0.2095	0.0939	0.2957	0.3449	0.1018	0.3801	0.4123	0.1009
	(1.36)	(1.42)	(1.69)	(1.58)	(1.72)	(1.85)	(1.76)	(2.14)	(2.32)	(1.97)	(3.04)	(3.56)	(3.06)	(4.92)	(4.53)
δ_3	−0.0038	−0.0029	−0.0180	0.00017	0.00013	−0.0034	0.00071	0.00012	−0.0095	−0.00004	−0.00005	0.9914	0.00002	0.00003	−0.0013
	(−1.95)	(−1.78)	(−1.93)	(1.31)	(0.80)	(−1.52)	(0.04)	(0.77)	(−1.35)	(−0.93)	(−1.44)	(1.29)	(0.66)	(1.18)	(−1.41)
δ_4	−0.0019	−0.00008	0.0098	−0.00010	−0.00008	0.0019	−0.00003	−0.00005	0.0061	−0.00003	0.00001	0.0078	−0.00011	−0.00001	0.0041
	(−2.03)	(−1.33)	(1.78)	(−1.18)	(−0.74)	(1.31)	(−0.62)	(−1.18)	(1.55)	(−1.07)	(0.62)	(1.20)	(−1.53)	(−1.05)	(1.13)
Panel B: Individual stocks/options in CVol–PVol portfolios															
γ_3	−0.0812	−0.0649	−0.0457	−0.1087	−0.1721	−0.0852	−0.1185	−0.2002	−0.1689	−0.1078	−0.1966	−0.1209	−0.1751	−0.2046	−0.1953
	(−1.46)	(−1.35)	(−1.61)	(−1.85)	(−1.93)	(−1.85)	(−2.11)	(−2.47)	(−2.74)	(−2.03)	(−2.97)	(−2.88)	(−2.26)	(−2.83)	(−3.28)
γ_4	0.0887	0.0762	0.0562	0.1335	0.2533	0.0962	0.2065	0.3173	0.1736	0.2451	0.3541	0.1231	0.3551	0.3996	0.1197
	(1.79)	(1.66)	(1.71)	(1.84)	(2.62)	(1.92)	(2.29)	(2.70)	(3.78)	(2.64)	(3.89)	(4.55)	(2.97)	(4.87)	(4.42)
δ_3	−0.00001	−0.00007	−0.0654	0.00005	−0.00003	−0.0305	0.00004	0.00031	−0.0509	0.00003	0.00017	−0.0043	−0.00006	0.00001	−0.0073
	(−0.22)	(−1.33)	(−2.15)	(1.12)	(−1.16)	(−1.36)	(0.90)	(1.28)	(−1.47)	(0.79)	(1.56)	(−1.07)	(−1.89)	(0.46)	(−0.91)
δ_4	−0.00003	0.00001	0.0100	−0.00026	0.000001	0.0081	−0.00006	−0.00007	0.0086	−0.00005	−0.00001	0.0069	−0.00008	−0.00001	0.0050
	(−1.12)	(0.48)	(2.11)	(−1.84)	(0.01)	(1.40)	(−1.02)	(−1.07)	(1.43)	(−1.51)	(−1.01)	(1.85)	(−1.84)	(−0.24)	(1.16)

Notes. This table presents the maximum likelihood estimates of the VAR-bivariate-GARCH model. The t-statistics are reported in parentheses.

options today reveals something about tomorrow's volatility in stocks.[26] Another notable point in Table 6 is that the average parameters and their statistical significance indicate that the information spillover is relatively stronger in the higher quintiles of volatility spreads.

8. Conclusions

We examine the relation between expected future volatility and the cross-section of expected returns over the sample period of February 1996 to January 2005. Unlike earlier studies that rely on the historical data, we focus on the market's expectation of future volatility of individual stocks, extracted from call and put option prices. We find that a trading strategy buying stocks in the highest implied (call or put) volatility quintile and shorting stocks in the lowest quintile (respectively, call or put) generates returns that are not significantly different from zero. These results are in contrast to the analysis of Ang et al. (2006), who use the one-month lagged realized volatility to proxy for expected volatility and find that high volatility portfolios generate unusually low returns. Because we are able to replicate the Ang et al. (2006) results in our sample, the failure of options' implied volatility based trading strategies is puzzling.

To further investigate the differences and interactions between alternative measures of volatility, we use the Fama-MacBeth (1973) methodology. The average slope coefficients from the firm-level cross-sectional regressions indicate that none of the three volatility measures (realized, call, and put implied volatility) shows a significant impact on the expected future returns when it is the only independent variable in the regression. With all three measures on the right-hand side, however, the effects of the realized and put implied volatilities on expected future returns are significantly negative, whereas the impact of the call implied volatility is significantly positive. This finding suggests that although the level of volatilities from the physical and risk-neutral distributions cannot predict future stock returns, there can be a significant relation between volatility spreads and the cross-section of expected returns.

We examine whether the realized-implied volatility spread and the call-put implied volatility spread can predict the cross-sectional variation in expected returns. Portfolio level analyses indicate that a trading strategy that longs stocks in the lowest RVol–IVol quintile and shorts stocks in the highest RVol–IVol quintile produces average returns in the range of 0.60% to 0.73% per month. A portfolio that longs stocks in the highest CVol–PVol quintile and shorts stocks in the lowest CVol–PVol quintile earns 1.05% to 1.49% per month. The average raw, risk-adjusted, and abnormal return differences between the highest and the lowest quintile portfolios of RVol–IVol and CVol–PVol are both economically and statistically significant. These results do not change when we control for the well-known cross-sectional effects including size and book-to-market, illiquidity and bid-ask spread, analyst forecast dispersion, probability of informed trading, physical and risk-neutral measures of skewness, and systematic risk proportion. In addition to the univariate and bivariate portfolio analyses, the significance of volatility spreads remains intact when we rely on the firm-level cross-sectional regressions (with and without controls).

Consistent with earlier studies performed at the market level, we find evidence that the realized-implied volatility spread is a proxy for volatility risk that has a significantly negative premium in the cross-sectional pricing of individual stocks. We compute the standard deviation of jump returns for the call-put implied volatility quintiles and jump risk is found to be higher for stocks with higher call-put implied volatility spread. The CVol–PVol spread proxying for jump risk has a significantly positive cross-sectional premium. Further analysis based on the bivariate portfolios of volatility spreads indicates that jump risk and volatility risk are priced differently and independently of each other.

This paper introduces a VAR-bivariate-GARCH model to test the significance of information spillover between the options and the stock markets. The maximum likelihood parameter estimates provides evidence that there is significant volatility spillover effect and information spills over from individual equity options to individual stocks, implying informed trading in options by investors with private information.

9. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

Acknowledgments
The authors thank David Hsieh (the department editor), the associate editor, and two anonymous referees for their extremely helpful comments and suggestions. The authors owe a great debt to David Weinbaum and Liuren Wu for their insightful comments and constructive criticisms on earlier versions of this paper. Both authors gratefully acknowledge the financial support from the PSC-CUNY Research Foundation of the City University of New York.

[26] We also investigate whether option volume is informative for the future volume and volatility of underlying stocks. The results in the online supplement indicate that trading volume in the options market leads stock index volume with a one-day lag. Similarly, trading volume of the S&P 500 index options is a statistically significant predictor of the one-day ahead realized volatility of the underlying S&P 500 index. A natural interpretation of this finding is that option volume is informative about future volatility of the underlying asset, and is also consistent with investors bringing volatility information to the options market.

References

Ait-Sahalia, Y. 2004. Disentangling diffusion from jumps. *J. Financial Econom.* **74** 487–528.

Ait-Sahalia, Y., J. Jacod. 2009. Testing for jumps in a discretely observed process. *Ann. Statist.* **37** 2202–2244.

Amihud, Y. 2002. Illiquidity and stock returns: Cross-section and time-series effects. *J. Financial Markets* **5** 31–56.

Andersen, T. G., T. Bollerslev, F. X. Diebold, P. Labys. 2003. Modeling and forecasting realized volatility. *Econometrica* **71** 579–626.

Ang, A., R. J. Hodrick, Y. Xing, X. Zhang. 2006. The cross-section of volatility and expected returns. *J. Finance* **61** 259–299.

Ang, A., R. J. Hodrick, Y. Xing, X. Zhang. 2009. High idiosyncratic volatility and low returns: International and further U.S. evidence. *J. Financial Econom.* **91** 1–23.

Bakshi, G., N. Kapadia. 2003a. Delta-hedged gains and the negative volatility risk premium. *Rev. Financial Stud.* **16** 527–566.

Bakshi, G., N. Kapadia. 2003b. Volatility risk premium embedded in individual equity options. *J. Derivatives* **16** 527–566.

Bakshi, G., N. Kapadia, D. Madan. 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. *Rev. Financial Stud.* **16** 101–143.

Bali, T. G., N. Cakici. 2008. Idiosyncratic volatility and the cross-section of expected returns. *J. Financial Quant. Anal.* **43** 29–58.

Bali, T. G., R. F. Engle. 2007. Investigating ICAPM with dynamic conditional correlations. Working paper, Baruch College, New York.

Banerjee, P. S., J. S. Doran, D. R. Peterson. 2007. Implied volatility and future portfolio returns. *J. Banking Finance* **31** 3183–3199.

Barberis, N., M. Huang. 2008. Stocks as lotteries: The implications of probability weighting for security prices. *Amer. Econom. Rev.* **98** 2066–2100.

Barndorff-Nielsen, O. E., N. Shephard. 2004. Econometric analysis of realized covariation: High frequency based covariance, regression and correlation in financial economics. *Econometrica* **72** 885–925.

Barndorff-Nielsen, O. E., N. Shephard. 2006. Econometrics of testing for jumps in financial economics using bipower variation. *J. Financial Econometrics* **4** 1–30.

Bates, D. 1996. Jumps and stochastic volatility: Exchange rate processes implicit in deutsche mark options. *Rev. Financial Stud.* **9** 69–107.

Bates, D. 2000. Post-'87 crash fears in S&P 500 futures options. *J. Econometrics* **94** 181–238.

Berndt, A., A. Ostrovnaya. 2007. Information flow between credit default swap, option, and equity markets. Working paper, Carnegie Mellon University, Pittsburgh.

Bollerslev, T., H. Zhou. 2006. Volatility puzzles: A unified framework for gauging return-volatility regressions. *J. Econometrics* **131** 123–150.

Chan, K., K. C. Chan, A. G. Karolyi. 1991. Intraday volatility in the stock index and stock index futures markets. *Rev. Financial Stud.* **4** 657–684.

Cherian, J., R. Jarrow. 1998. Option markets, self-fulfilling prophecies, and implied volatilities. *Rev. Derivatives Res.* **2** 5–37.

Chernov, M. 2007. On the role of risk premia in volatility forecasting. *J. Bus. Econom. Statist.* **25** 411–426.

Chernov, M., A. R. Gallant, E. Ghysels, G. Tauchen. 2003. Alternative models of stock price dynamics. *J. Econometrics* **116** 225–257.

Coval, J., T. Shumway. 2001. Expected option returns. *J. Finance* **56** 983–1009.

Cox, J. C., M. Rubinstein. 1985. *Option Markets*. Prentice Hall, Upper Saddle River, NJ.

Cox, J. C., S. A. Ross, M. Rubinstein. 1979. Option pricing: A simplified approach. *J. Financial Econom.* **7** 229–263.

Cremers, M., D. Weinbaum. 2009. Deviations from put-call parity and stock return predictability. *J. Financial Quant. Anal.* Forthcoming.

Diavatopoulos, D., J. S. Doran, D. R. Peterson. 2008. The information content in implied idiosyncratic volatility and the cross-section of stock returns: Evidence from the option markets. *J. Futures Markets* **28** 1013–1039.

Diether, K. B., C. J. Malloy, A. Scherbina. 2002. Differences of opinion and the cross section of stock returns. *J. Finance* **57** 2113–2141.

Duan, J.-C., J. Wei. 2009. Systematic risk and the price structure of individual equity options. *Rev. Financial Stud.* **22** 1981–2006.

Easley, D., M. O'Hara. 2004. Information and the cost of capital. *J. Finance* **59** 1553–1583.

Easley, D., S. Hvidkjaer, M. O'Hara. 2002. Is information risk a determinant of asset returns? *J. Finance* **57** 2185–2221.

Easley, D., M. O'Hara, P. Srinivas. 1998. Option volume and stock prices: Evidence on where informed traders trade. *J. Finance* **53** 431–465.

Eraker, B., M. Johannes, N. G. Polson. 2003. The impact of jumps in returns and volatility. *J. Finance* **53** 1269–1300.

Fama, E. F., K. R. French. 1992. Cross-section of expected stock returns. *J. Finance* **47** 427–465.

Fama, E. F., K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *J. Financial Econom.* **33** 3–56.

Fama, E. F., J. D. MacBeth. 1973. Risk and return: Some empirical tests. *J. Political Econom.* **81** 607–636.

Fu, F. 2009. Idiosyncratic risk and the cross-section of expected stock returns. *J. Financial Econom.* **91** 24–37.

Harvey, C., A. Siddique. 2000. Conditional skewness in asset pricing tests. *J. Finance* **55** 1263–1295.

Heston, S. 1993. A closed-form solution of options with stochastic volatility with applications to bond and currency options. *Rev. Financial Stud.* **6** 327–343.

Jackwerth, J., M. Rubinstein. 1996. Recovering probability distributions from option prices. *J. Finance* **51** 1611–1631.

Jiang, G., R. Oomen. 2008. Testing for jumps when asset prices are observed with noise—A "swap variance" approach. *J. Econometrics* **144** 352–370.

Johannes, M. 2004. The statistical and economic role of jumps in continuous-time interest rate models. *J. Finance* **59** 227–260.

Kawaller, I., P. Koch, T. Kock. 1987. The temporal price relationship between S&P 500 futures and S&P 500 index. *J. Finance* **42** 1309–1329.

Merton, R. C. 1976. Option pricing when underlying stock returns are discontinuous. *J. Financial Econom.* **3** 125–144.

Miller, E. 1977. Risk, uncertainty, and divergence of opinion. *J. Finance* **32** 1151–1168.

Nandi, S. 1999. Asymmetric information about volatility: How does it affect implied volatility, option prices and market liquidity? *Rev. Derivatives Res.* **3** 215–236.

Nelson, D. B. 1991. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica* **59** 347–370.

Newey, W. K., K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* **55** 703–708.

Ofek, E., M. Richardson, R. Whitelaw. 2004. Limited arbitrage and short sales restrictions: Evidence from the options markets. *J. Financial Econom.* **74** 305–342.

Pan, J. 2002. The jump-risk premia implicit in options: Evidence from an integrated time-series study. *J. Financial Econom.* **63** 3–50.

Spiegel, M., X. Wang. 2005. Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk. Working paper, Yale International Center for Finance, New Haven, CT.

Stoll, H., R. Whaley. 1990. The dynamics of stock index and stock index futures returns. *J. Financial Quant. Anal.* **25** 441–468.

Xing, Y., X. Zhang, R. Zhao. 2009. What does individual option volatility smirks tell us about future equity returns? *J. Financial Quant. Anal.* Forthcoming.