Volatility Spreads and Expected Stock Returns

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ABSTRACT

We examine the relation between expected future volatility (options' implied volatility) and the cross-section of expected returns. A trading strategy buying stocks in the highest implied volatility quintile and shorting stocks in the lowest implied volatility quintile generates insignificant returns. A similar strategy using one-month lagged realized volatility generates significantly negative returns. To investigate the differences and interactions between alternative measures of total risk, we estimate three principal components based on realized volatility, call implied and put implied volatility. Long-short trading strategies generate significant returns only for the second and the third principal components. We find that the second principal component is related to the realized-implied volatility spread which can be viewed as a proxy for volatility risk. We find that the third principal component is related to the call-put implied volatility spread that reflects future price increase of the underlying stock.

JEL classification: G10, G11, G12, G14

Key words: total volatility, realized volatility, implied volatility, stock returns.

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We examine the relation between expected future volatility (options' implied volatility) and the cross-section of expected returns. A trading strategy buying stocks in the highest implied volatility quintile and shorting stocks in the lowest implied volatility quintile generates insignificant returns. A similar strategy using one-month lagged realized volatility generates significantly negative returns. To investigate the differences and interactions between alternative measures of total risk, we estimate three principal components based on realized volatility, call implied and put implied volatility. Long-short trading strategies generate significant returns only for the second and the third principal components. We find that the second principal component is related to the realized-implied volatility spread which can be viewed as a proxy for volatility risk. We find that the third principal component is related to the call-put implied volatility spread that reflects future price increase of the underlying stock.

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1. Introduction

If investors held all the risky securities available in the market, the expected return of an individual stock would be determined solely by its contribution to the risk of the market portfolio (i.e., only systematic risk would affect expected returns). However, with a constraint on the number of securities in a portfolio, idiosyncratic risk becomes an important component of investors' decision making process as it affects total risk of the portfolio.[1] Several asset pricing models, e.g., Levy (1978) and Merton (1987), show that, limited diversification results in an equilibrium where expected returns compensate not only for market risk but also for idiosyncratic risk. Motivated by these theoretical models and investors' preferences for holding less than perfectly diversified portfolios, recent empirical studies investigate the cross-sectional relation between expected stock returns and idiosyncratic and total volatility.

Using daily return data, Ang, Hodrick, Xing and Zhang (AHXZ, 2006) measure monthly idiosyncratic volatility of individual stocks based on the three-factor Fama-French (1993) model and examine the returns on portfolios of stocks sorted by idiosyncratic volatility. Contrary to most theoretical models, AHXZ indicate a strong negative relation between idiosyncratic volatility and expected stock returns. Fu (2005) and Spiegel and Wang (2005) use conditional measures of idiosyncratic volatility and find a positive and significant relation between idiosyncratic risk and expected returns.

Bali and Cakici (2006) focus on the methodological differences that led the previous studies to develop conflicting evidence. They show that data frequency used to estimate idiosyncratic and total risk, weighting scheme adopted for generating average portfolio returns, breakpoints utilized to sort stocks into quintile (or decile) portfolios, and using a screen for size, price and liquidity play a critical role in determining the significance of a cross-sectional relation between expected returns and volatility.

To summarize, the existence and the direction of the relation between volatility and the cross-section of expected stock returns is a subject of an intense debate. Although some studies find a positive link between volatility and expected returns at the firm or portfolio level, often the cross-sectional relation has been found insignificant, and sometimes even negative.[2]

This paper examines the relation between "expected future volatility" and the cross-section of expected returns. The aforementioned earlier studies on volatility generally use the past behavior of asset prices to develop expectations about future volatility, modeling movements in volatility as they relate to prior

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[1] The typical investor usually does not hold many risky assets in her portfolio for various reasons, such as transaction costs, incomplete information, indivisibility of investment, institutional restrictions, liquidity constraints, or any other exogenous reasons. For example, Blume and Friend (1975) find that the average number of securities held in a portfolio of typical investor is about 3.41. Barber and Odean (2000) report that the mean household's portfolio contains only 4.3 stocks and the median household invests in 2.61 stocks. Both studies indicate that most individuals hold very small number of stocks in their portfolios.

[2] Both AHXZ (2006) and Bali and Cakici (2006) find the cross-sectional predictive power of idiosyncratic and total risks to be very similar.

volatility and/or other variables in the investors' information set. AHXZ (2006) 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 (2006) use the past 60 months of individual stock returns to generate one-month ahead total volatility. Spiegel and Wang (2005) and Fu (2005) define the conditional volatility of individual stocks as a function of the past residuals and the past volatility based on the exponential GARCH (EGARCH) model of Nelson (1991). In contrast to these studies, we focus on the market's expectation of future volatility of individual stocks.

We use the reported call and put option prices to infer volatility expectations.[3] We obtain option implied volatilities over the sample period of January 1996 to December 2004 and test whether the call and put implied volatilities of individual stocks can predict the cross-sectional variation in stock returns. The results provide no evidence for a significant link between expected returns and expected future volatility (call and put implied volatility) during our sample period.

We also replicate in our sample the analysis of AHXZ (2006) by proxying expected volatility with the one-month lagged realized volatility (RVol) defined as the standard deviation of daily returns over the past one month. Similar to their findings, stocks with low (high) realized volatility earn high (low) average raw and risk-adjusted returns. However, the negative relation does not seem to be robust in terms of statistical significance.

With different measures of volatility having such different effects on stock returns, the explanation for the effects of different volatility measures on stock returns could be found by identifying the common and orthogonal components of these measures. We, therefore, investigate the differences and the commonalities between alternative measures of total risk by estimating the principal components of realized and implied volatilities. The first principal component (PC1) is found to be positively correlated with the three volatility measures (realized volatility, call implied volatility, and put implied volatility). The second principal component (PC2) turns out to be positively related to realized volatility, but is negatively related to both implied volatilities. The third principal component (PC3) is positively linked to call implied volatility, negatively linked to put implied volatility, and has almost no association with realized volatility.

We examine the cross-sectional relation between expected returns and the principal components of volatility for the NYSE/AMEX/NASDAQ stocks as well as for the NYSE stocks only. The differences in average returns (both raw and risk-adjusted) of the highest PC1 quintile portfolio and the lowest PC1 quintile portfolio generally indicate a negative, but statistically insignificant relation between PC1 and expected returns. The results generally provide a negative and significant link between PC2 and the cross-section of stock returns. A trading strategy that longs stocks in the lowest PC2 quintile and shorts stocks in

[3] Since option value depends critically on expected future volatility, the volatility expectation of market participants can be recovered by inverting the option valuation formula such as the closed-form solution of Black and Scholes (1973) or the binomial tree model of Cox, Ross, and Rubinstein (1979).

the highest PC2 quintile produces average raw and risk-adjusted returns in the range of 50 to 90 basis points per month. The univariate portfolio-level analyses indicate a positive and significant cross-sectional relation between PC3 and expected returns. A portfolio that longs stocks in the highest PC3 quintile and shorts stocks in the lowest PC3 quintile earns 1.1% to 1.4% per month and these average raw and risk-adjusted return differences are highly significant with the t-statistics greater than 3.0.

We also control for the well-known cross-sectional effects including size and book-to-market (Fama and French (1992, 1993)), liquidity and bid-ask spread (Amihud (2002)), analyst forecast dispersion (Diether, Malloy, and Scherbina (2002)), probability of informed trading (Easley, Hvidkjaer, and O'Hara (2002)), and skewness (Harvey and Siddique (2000)). After controlling for these effects in bivariate sorts of portfolios, our main findings remain to be strong with the cross-sectional premium of PC2 (PC3) being negative (positive) and highly significant.

In addition to the univariate and bivariate sorts of long-short portfolios, we examine the cross-sectional relation between PC1, PC2, and PC3 and expected returns using the firm-level Fama-MacBeth (1973) regressions. These regression results show a significantly negative (positive) relation between PC2 (PC3) and the cross-section of expected returns. The results remain intact after controlling for size, book-to-market, liquidity, analyst forecast dispersion, probability of informed trading, and skewness.

Motivated by our findings of significant predictive power of these principal components with respect to future returns, we next investigate the factors underlying these principal components. Specifically, the positive correlation of PC2 with realized volatility and its negative correlation with both implied volatilities suggests that PC2 could be related to the realized-implied volatility spread (RVol-IVol). Similarly, PC3 could be related to the call-put implied volatility spread (CVol-PVol). Indeed, we find that the correlations between (RVol-IVol) and PC1, PC2, and PC3 are, respectively, 0.153, 0.896, and -0.001, implying that PC2 is largely the same as (RVol-IVol).[4] The correlations between (CVol-PVol) and PC1, PC2, and PC3 are -0.030, -0.003, and 0.937, respectively. These sample correlations imply that PC3 can be viewed as almost identical to (CVol-PVol).

A high call-put implied volatility spread (CVol-PVol>0) indicates that the call option prices exceed the levels implied by the put option prices and the put-call parity. Ofek, Richardson, and Whitelaw (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), consistent with our results.

[4] The implied volatility here is calculated using both call and put options.

The negative relation between the realized-implied volatility spread (RVol-IVol) and future stock returns could be due to (RVol-IVol) proxying for innovations in individual stock volatilities. In the intertemporal capital asset pricing model (ICAPM) of Merton (1973), investors want to hedge against unfavorable shifts in the investment opportunity set. Campbell (1993, 1996) has a theoretical framework in which "innovations in aggregate volatility" are viewed as deterioration in investment opportunities (or unfavorable shift in the investment opportunity set).[5] Campbell shows that investors want to hedge against innovations in aggregate volatility because increasing volatility (or increase in the difference RVol-IVol) represents deterioration in investment opportunities. Risk-averse investors demand stocks that hedge against this volatility risk. This leads to a negative relation between expected stock returns and high covariance with innovations in market volatility. That is, stocks with higher correlation with (RVol-IVol) are expected to yield lower return.

Since Campbell's (1993, 1996) two-factor ICAPM predicts both a time-series and cross-sectional relation between expected returns and risk, we assume that stocks with high sensitivities to innovations in total volatility provide hedges against deterioration in investment opportunity set. Investors increase their demand for these stocks because they serve as a hedging instrument. The higher demand for these stocks increases their price and lowers their expected return. Put differently, investors would be willing to accept lower expected return (or lower compensation) from holding stocks with high sensitivities to innovations in total volatility.

The paper is organized as follows. Section 2 discusses the data and our sample. Section 3 examines the relation between realized and implied volatilities and the cross section of expected returns. Section 4 estimates the principal components of volatilities and examines the relation between these principal components and the cross section of stock returns. Section 5 provides a battery of robustness checks after controlling for various well-known cross-sectional effects. Section 6 discusses the interpretations of our results. Section 7 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

[5] Innovations in aggregate volatility can be proxied by the difference between realized and implied volatility of market returns since realized volatility is a consistent estimator of actual underlying volatility and implied volatility is an estimator of expected future volatility: Innovation in Volatility = Actual Volatility – Expected Volatility (see Andersen, Bollerslev, Diebold, and Labys (2003)).

[6] To minimize the influence of outliers, financial ratios calculated using Compustat data are trimmed at values representing their first and the ninety-ninth percentiles.

factors (Rm-Rf, SMB, and HML) for the three-factor Fama-French 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 3 months, with positive open interest, positive best bid price, and non-missing implied volatility. We further delete options with bid-ask spreads exceeding fifty percent 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

A. 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 on stock returns in the cross-section presented by Ang, Hodrick, Xing, and Zhang (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 reports the results for all stocks with return and volatility data available, a total of 561,709 monthly observations. Panel B reports the results for the subset of optionable stocks, i.e., stocks with traded options. These results are based on 197,362 monthly returns, or about 35 percent of the overall sample.

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. The reported t-statistics are the Newey-West (1987) t-statistics with six lags.

Similar to Ang, Hodrick, Xing, and Zhang (2006), the results in Panel A show that the average monthly return increases from 0.9% per month to 1.0% percent per month as we move from quintile 1 (lowest-volatility quintile) to quintile 3. From there, the average returns drop. The average return for the highest-

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

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

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

volatility portfolio (quintile 5) is –0.3% per month. The FF-3 alpha for this portfolio (not reported) is −1.5% per month with a highly significant t-statistic of 3.2.

The results in the last two rows of Panel A show that the average monthly return on "5-1" arbitrage portfolio is economically large (−1.1%), though it is not statistically significant. The FF-3 alpha for the arbitrage portfolio is even larger (−1.5%) and it is highly significant with a t-statistic of −2.8. These numbers are comparable to those in Ang, Hodrick, Xing, and Zhang (2006), who report an average monthly return of −1.0% and the FF-3 alpha of −1.2% for the arbitrage portfolio in their longer sample period (July 1963-December 2000).

The next three columns report the average market share, market capitalization, book-to-market ratio, and realized volatility of stocks in the quintile portfolios. The average market share of our quintile portfolios are very similar to those reported in Ang, Hodrick, Xing, and Zhang (2006), where they vary between 41.7% for portfolio 1 and 2.4% for portfolio 5. The book-to-market ratios are somewhat lower in our sample, likely reflecting the higher valuation multiples of late 1990s. It is important to note that given that quintile 5 stocks are generally smaller and have higher book-to-market ratios, they should exhibit higher, not lower, average returns according to the Fama-French three factor model.

The patterns of the quintile portfolio and arbitrage portfolio returns do not change when only stocks with traded options are used to form realized volatility quintile portfolios (Panel B, Table 1). The average arbitrage portfolio return is −1.2% and the alpha is −1.6%. The comparison of market capitalizations shows that optionable stocks tend to be larger. Nevertheless, the distribution of relative market shares across the quintile portfolios in Panel B is very similar to that for the overall sample (Panel A). On the other hand, the pattern of book-to-market ratios is reversed in Panel B. The book-to-market ratios now decline across the realized volatility quintiles. Panel B reports two additional columns representing the average values of call implied volatility and put implied volatility for stocks in the quintile portfolios. Not surprisingly, both implied volatilities increase monotonically across the realized volatility quintiles.

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

B. 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 A and B of Table 2 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 Table 1. However, the returns and the FF-3 alphas on arbitrage portfolios formed based on 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 given the monotonically increasing patterns of total and implied volatilities across realized volatility (in Panel B, Table 1), call implied volatility (in Panel A, Table 2), and put implied volatility (in Panel B, Table 2) quintiles.

4. Principal components of volatility and stock returns

A. Principal components

The differences in the results for realized and implied volatility portfolios should be due to the orthogonal components of realized and implied volatilities. To better understand what drives the negative relation between realized volatility and future returns, we use principal component analysis to transform our original three volatility measures into three new variables, PC1, PC2, and PC3. These new variables are linear transformations of the original variables and are orthogonal to each other. The variables are constructed such that the first principal component, PC1, absorbs most of the variation in the original variables, the second component, PC2, absorbs most of the remaining variation, and the third component, PC3, absorbs the remainder.

We estimate the principal components each month based on the realized volatility over the previous month and the volatilities implied by call and put option prices observed at the end of the previous month. Monthly estimation of the principal components allows us to use them to construct trading strategies based on the principal components of volatility.

Table 3 presents the full sample correlations between the principal components and the original volatility variables. The coefficients of correlation show that PC1 is highly positively correlated with all three volatility measures. Furthermore, in each of the 108 months, the linear coefficients linking the three volatility measures with PC1 are always positive. The coefficients of correlation also show that PC2 is positively related to realized volatility but is negatively related to both implied volatilities. Furthermore, in each of the 108 months, the linear coefficients linking realized (call implied) volatility with PC2 are positive (negative). For put implied volatility, the linear coefficients linking it with PC2 are negative in 107 of 108 months. Finally, the correlations imply that PC3 is positively related to call implied volatility, negatively related to put implied volatility, and pretty much unrelated to realized volatility. The negative relation between put implied volatility and PC3 holds in each of 108 months, whereas the positive relation between call implied volatility and PC3 holds for 107 of 108 months. These results imply that the correspondence between the principal components and the underlying economic forces is likely to be quite stable.

B. Principal components and the cross-section of stock returns

We next repeat our analysis of the relation between volatility and stock returns for quintile portfolios formed on the basis of principal components of volatility. Each month, we sort all stocks into quintile portfolios based on PC1, PC2, and PC3. Thus, for each value-weighted quintile portfolio we have a series of 108 monthly returns, which we use to calculate the average monthly portfolio returns as well as alphas with respect to the Fama-French (1993) three-factor model.

The results are presented in Table 4. The results for PC1-based portfolios in Panel A are mixed. The overall pattern of average monthly returns across quintile portfolios is similar to the pattern for the realized volatility portfolios in Table 1. However, neither the returns, nor the FF-3 alphas of the arbitrage portfolios are significantly different from zero. The size and book-to-market ratios of portfolios sorted on PC1 exhibit patterns that are qualitatively similar to the patterns for realized volatility portfolios of optionable stocks, but in terms of actual numbers, are closer to the patterns for implied volatility portfolios.

The results for PC2 quintile portfolios are presented in Panel B of Table 4. Unlike for volatility portfolios in Tables 1 and 2 and for PC1 portfolio in Panel A of Table 4, the pattern of average monthly returns across PC2 quintiles is more monotonic. The highest return (1.5% per month) is observed for quintile 2 and the lowest return (0.5% percent per month) is observed for quintile 5. The FF-3 alphas exhibit similar patterns. The return on "5-1" arbitrage portfolio is −0.9% per month with a Newey-West t-statistic of −1.9, and the FF-3 alpha is −0.8% per month with a t-statistic of 2.0.

The market share, size, and book-to-market ratios of the quintile portfolios sorted by PC2 display inverted U-shaped patterns, unlike the patterns observed for other volatility portfolios. Stocks in quintiles 1 and 5 are smaller and they have smaller market shares and book-to-market ratios than firms in quintiles 3 and 4. Overall, however, the distribution of these values across PC2 quintiles is more even than for the corresponding distribution for PC1 and realized and implied volatility quintiles. The distributions of realized volatility and call and put implied volatilities across PC2 quintiles are also U-shaped. The highest realized volatility is observed for PC2 quintile 5, whereas the highest implied volatilities are observed for quintile 1, which is expected since PC2 is positively related to realized volatility and negatively related to both implied volatilities by construction.

Panel C of Table 4 presents the results for PC3 quintile portfolios. The returns increase monotonically from 0.2% per month for quintile 1 to 1.4% per month for quintile 5. The returns and FF-3 alphas for arbitrage portfolio returns are economically large (1.2-1.3% per month) and highly significant with the t-statistics equal or greater than 3.7. The average market share and size of PC3 quintile portfolios display an inverted U-shaped pattern, whereas the book-to-market ratio displays a U-shaped pattern across quintiles.

C. Principal components and the cross-section of stock returns: NYSE stocks

In this section, we repeat the analysis of the relation between the principal components of volatility and returns for NYSE stocks. Although all quintile portfolios contain 20% of the stocks, some of the extreme quintiles that generate the bulk of abnormal returns represent only a small fraction of the value of the "market". For example, quintile 5 that contains the highest PC1 stocks, represents only 3.6 percent of market value of all PC1 stocks. It is possible that the evidence presented thus far may be driven by small and illiquid stocks. To confirm the robustness of our results, we repeat our analysis for the stocks that are traded on the NYSE. Furthermore, the trading profits that are generated by this subsample are closer to what can actually be captured by investors due to relatively low transaction costs and higher implementability.

The results are presented in Table 5. In addition to calculating value-weighted portfolio returns for the next month, we also calculate equal-weighted returns. As an additional robustness check, we also report the abnormal portfolio returns, AR, calculated relative to characteristic-matched benchmark portfolios. For this, we use twenty-five benchmark portfolios formed based on the market value of equity (ME) and book-to-market of equity (BM).[10] 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.

Panel A reports the results for quintile portfolios sorted by PC1. For the value-weighted portfolios, the returns for quintile 5 are now equal to the returns for quintile 1. For the equal-weighted portfolios, the returns of quintile 5 stocks are slightly higher than the returns of quintile 1 stocks. Although the FF-3 alphas are still lower for quintile 5 portfolios, the differential returns, ARs, and FF-3 alphas of all arbitrage portfolios are statistically indistinguishable from zero for the NYSE stocks.

The results for PC2 quintile portfolios (Panel B) and PC3 quintile portfolios (Panel C) remain significant as we limit our attention to the NYSE stocks. The PC2 arbitrage portfolio returns, ARs, and FF-3 alphas are in the range of –0.5% to –0.7% per month, with all the values statistically significant, except FF-3 alpha for value-weighted arbitrage portfolio, whose t-statistic = –1.9 implies marginal significance. The PC3 arbitrage portfolio returns, ARs, and FF-3 alphas are also all statistically significant and are similar in magnitude (1.1%-1.4% per month) to the corresponding returns in Table 4.

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[10] ME is the price times shares outstanding. Following Davis, Fama, and French (2000), BE is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. Stockholders' equity is the value reported by Compustat, if it is available. If not, we measure stockholders' equity as the book value of common equity plus the par value of preferred stock, or the book value of assets minus total liabilities (in that order).

The distributions of average market share, size, and book-to-market across quintiles in all panels of Table 5 are qualitatively similar to the distributions in Table 4, except the extreme quintile portfolios in Table 5 represent a larger market share of NYSE. Not surprisingly, for most quintile portfolios, the average size and the average book-to-market ratios in Table 5 are larger than the corresponding values in Table 4, reflecting the fact that firms traded on the NYSE are on average larger and more mature than stocks traded on the NASDAQ.

To summarize, of the three principal components formed on the basis of realized volatility and call and put implied volatilities, sorting on the first principal component does not generate a significant return differential between low and high quintile portfolios. In contrast, arbitrage portfolios formed based on sorting on the second and the third principal components generate statistically and economically significant returns. These results hold when we limit our attention to NYSE stocks, when we control for risk, and both for value-weighted and equal-weighted portfolios.

5. Controlling for other cross-sectional effects

In this section, we examine whether the significant relations between the second and the third principal components and returns persist once we control for various cross-sectional effects identified in the earlier literature as factors with significant impact on returns.[11] Unlike in earlier tests, we form PC 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, Hodrick, Xing, and Zhang (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 PC2 (Panel A) or PC3 (Panel B). Each characteristic quintile, thus, contains five PC quintiles. Next, PC quintiles 1 from each control characteristic quintile are averaged into a single quintile 1, PC quintiles 2 are averaged into a single quintile 2, etc. The resulting PC quintiles contain stocks with all values of the characteristic and, hence, represent PC quintile portfolios controlling for the characteristic. In Table 6, we report the returns, ARs, and FF-3 alphas of the "5-1" arbitrage portfolios formed on the basis of these quintiles.

A. Controlling for Size and Book-to-Market

Although the characteristic-matched abnormal returns (AR) 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 PC2 and PC3 portfolios are formed controlling for size. Both for PC2 and PC3, the returns, ARs, and FF-3 alphas of both the equal-weighted

[11] The results for PC1 portfolios remain insignificant in the presence of all controls and are not reported for brevity.

and value-weighted arbitrage portfolios remain economically large and statistically significant. These results imply that size explains neither the PC2 effect, nor the PC3 effect.

The second line in each panel represents the arbitrage portfolio returns when PC2 and PC3 portfolios are formed controlling for book-to-market. Both for PC2 and PC3, 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 PC2 and PC3 effects.

B. Controlling for Illiquidity

We next use Amihud's (2002) illiquidity measure as a control variable.[12] Amihud finds that illiquid stocks earn higher returns. The bivariate portfolio results, reported in the third rows of Panels A (PC2) and B (PC3), show that the significant returns on PC2 and PC3 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 between –0.6% and –0.8% per month for PC2, and between 1.4% and 1.5% per month for PC3. All the returns are statistically significant.

C. 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 PC2 arbitrage portfolios are –0.5% with equal weighting and –0.9% with value weighting. FF-3 alphas for PC3 arbitrage portfolios are 1.4% per month with either portfolio weighting scheme.

D. Controlling for Analyst Forecast Dispersion

Our next control variable is the analyst forecast dispersion, calculated as the standard deviation of the analysts' forecasts of the next fiscal year's earnings per share scaled by the mean analyst forecast.[13] Diether, Malloy, and Scherbina (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.

[12] 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.

[13] These variables come from the IBES summary of estimates file.

The results controlling for analyst forecast dispersion 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 PC2 based FF-3 alphas, for example, are –0.8% for the value-weighted portfolio and –0.7% for the equal-weighted portfolio. The PC3 based FF-3 alphas are 1.4% for both the value-weighted and the equal-weighted portfolios.

E. Controlling for Informed Trading

Easley and O'Hara (2000) present a model showing that private information-based trading affects the cross-section of expected returns. Easley, Hvidkjaer, and O'Hara (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.

Using the PIN as a control variable, we investigate whether the predictability from PC2 and PC3 is driven by their correlation with concentration of informed traders.[14] These results are reported in the sixth rows of Panels A and B of Table 6. Controlling for PIN does affect the returns of value-weighted PC2 arbitrage portfolios, which decline in magnitude and become insignificant at the five percent level. The equal-weighted arbitrage portfolio returns, however, remain significant. The equal-weighted FF-3 alpha is –0.6% per month, which is similar to our earlier findings from the univariate portfolios. Controlling for PIN does not affect the returns on PC3 arbitrage portfolios. The returns, ARs, and FF-3 alphas, all remain large and significant.

F. Controlling for Skewness

Our final control variable is skewness.[15] Harvey and Siddique (2000) show that coskewness with the market has a significant impact on expected returns. Barberis and Huang (2005) 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 6. Although controlling for skewness does not affect the arbitrage returns and ARs of PC2 portfolios, the FF-3 alpha of the value-weighted arbitrage portfolio becomes marginally significant with t-stat. = –1.8. For PC3 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 1.3% for the equal-weighted portfolio, and both alphas are highly significant.

[14] We downloaded NYSE stock PIN values from Soeren Hvidkjaer's website. The data are annual and are available through 2001. Since 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.

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

G. 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. Table 7 reports the time-series averages of the slope coefficients from the monthly cross-sectional regressions and their Newey-West adjusted t-statistics.

The first regression contains only the principal components as independent variables. Consistent with our earlier results, the effect of PC1 is insignificant, the effect of PC2 is significantly negative, and the effect of PC3 is significantly positive. The second regression introduces controls for size and book-to-market in the form of natural logs of these variables. The third regression, introduces additional controls for illiquidity, analyst forecast dispersion, PIN, and skewness. The effects of PC2 and PC3 remain statistically significant. Among the control variables, only analyst forecast dispersion can significantly predict the cross-sectional variation in stock returns, with higher dispersion associated with lower returns, consistent with earlier studies.

6. Interpretation of the results

Our results thus far imply that the existence of a significant relation between the second and the third principal components of realized, call, and put implied volatilities and the cross-section of expected returns. We now turn our attention to identifying the economic factors underlying these principal components.

A. Principal Components of Volatility and their Observable Counterparts

As reported in Table 3, PC2 is positively correlated with realized volatility and negatively with both call and put implied volatilities. Therefore, it is plausible that PC2 could be related to the spread between the realized volatility and the average implied volatility calculated using both put and call options (RVol-IVol). Table 3 also reports that PC3 is positively related to call implied volatility, negatively to put implied volatility, and is essentially unrelated to realized volatility. This suggests that PC3 could be related to the spread between call and put implied volatilities (CVol-PVol).

Panels A and B of Table 8 provide evidence supporting these conjectures. Panel A reports the distributions of realized-implied volatility spread (RVol-IVol) and the call-put implied volatility spread (CVol-PVol) across PC1, PC2, and PC3 quintiles. There is very little variation in CVol-PVol across PC1 and PC2 quintiles with the differences between quintiles 5 and 1 (-0.002 for both PC1 and PC2) economically trivial and statistically insignificant. In contrast, CVol-PVol monotonically increases across PC3 quintiles such that the difference between quintiles 5 and 1 (0.093) is economically and statistically significant.

There is very little variation in RVol-IVol across PC3 quintiles with the differences between quintiles 5 and 1 (-0.003) economically and statistically insignificant. The variation across PC1 quintiles is more pronounced generating a statistically significant difference between quintiles 5 and 1. However, the difference (0.038) is economically small when compared with the difference generated by PC2 quintiles (0.317).

To summarize, the results in Panel A support our conjectures that PC2 primarily reflects the spread between the realized and implied volatilities, whereas PC3 primarily reflects the spread between the call and put implied volatilities. These conclusions are further supported by results in Panel B, which presents the correlation coefficients of PC1, PC2, and PC3 with RVol-IVol and CVol-PVol. The correlation of CVol-PVol with PC3 is very high (0.937) whereas its correlations with PC1 and PC2 are trivial (-0.030 and -0.003, respectively). The correlation of RVol-IVol with PC2 is also quite high (0.896), whereas the correlation with PC2 (0.153) is much smaller and the correlation with PC3 (-0.001) is essentially zero.

B. *An Interpretation of the Realized-Implied Volatility Spread*

Merton (1973)'s ICAPM implies the following equilibrium relation between risk and return,

$$\mu_i - r = A \cdot \sigma_{im} + B \cdot \sigma_{ix}, \tag{1}$$

where $\mu_i - r$ denotes the expected excess return on risky asset *i*, *A* reflects the average risk aversion of market investors, σ_{im} denotes the covariance between the excess return on asset *i* and the excess return on the market portfolio, *B* measures the market's reaction to shifts in a state variable *x* that governs the stochastic investment opportunity, and σ_{ix} measures the covariance between excess returns on the risky asset *i* and the state variable *x*.

Equation (1) states that in equilibrium, investors are compensated in terms of expected return, for bearing market (systematic) risk, and for bearing the risk of unfavorable shifts in the investment opportunity set.

The second term, $B \cdot \sigma_{ix}$, in equation (1) reflects the investors' demand for the asset as a vehicle to hedge against "unfavorable" shifts in the investment opportunity set. An "unfavorable" shift in the investment opportunity set variable *x* is defined as a change in *x* such that future consumption *c* will fall for a given level of future wealth. That is, an unfavorable shift is an increase in *x* if $\partial c{=}\partial x < 0$ and a decrease in *x* if $\partial c{=}\partial x > 0$.

Merton (1973) shows that all risk-averse utility maximizers will attempt to hedge against such shifts in the sense that if $\partial c{=}\partial x < 0$ ($\partial c{=}\partial x > 0$), then, ceteris paribus, they will demand more of the i^{th} asset, the more positively (negatively) correlated its return is with changes in *x*. Thus, if the ex-post opportunity set is less favorable than was anticipated, the investor will expect to be compensated by a higher level of wealth through the positive correlation of the returns. Similarly, if the ex post returns are lower, he will expect a more favorable investment environment.

Campbell (1993, 1996) provides a two-factor model in which "unexpected increase in market volatility" represents deterioration in the investment opportunity set (or decrease in optimal consumption). In this setting, a positive covariance of returns with volatility shocks (or innovations in market volatility) predicts a lower return on the stock. In the context of Campbell's ICAPM, an increase in volatility predicts a decrease in optimal consumption and hence an unfavorable shift in the investment opportunity set. Risk-averse investors will demand more of the i^{th} asset, the more positively correlated its return is with changes in volatility because they will be compensated by a higher level of wealth through positive correlation of the returns. That asset can be viewed as a hedging instrument. In other words, an increase in the covariance of returns with volatility risk leads to an increase in the hedging demand, which in equilibrium reduces expected return on the asset.

Following Campbell, we assume that investors want to hedge against unexpected change in market volatility defined as the difference between realized market volatility (RV^m) and implied market volatility (IV^m), i.e., unexpected market volatility = $RV^m - IV^m$. We test whether stocks that have higher correlation with $x = (RV^m - IV^m)$ would yield lower expected return.[16]

As discussed in the online supplement, we first estimate the time-varying conditional covariances between the excess returns on Dow 30 stocks and the excess return on the market portfolio, $\sigma_{im,t+1}$, and also the conditional covariances between the excess returns on Dow 30 stocks and unexpected news in market volatility, $\sigma_{ix,t+1}$. Then, we use panel data regressions and estimate the common slope coefficients on $\sigma_{im,t+1}$ and $\sigma_{ix,t+1}$, i.e., *A* and *B* in equation (1). As shown in Table I and II of the online supplement, the common slope coefficient *A* on $\sigma_{im,t+1}$ is estimated to be positive, whereas the common slope *B* on $\sigma_{ix,t+1}$ is estimated to be negative. Both *A* and *B* turn out to be highly significant, both economically and statistically. Overall, the results indicate a positive (negative) and significant relation between expected return and market risk (volatility risk). Based on the stacked time-series and pooled panel regressions, we find that stocks that have higher correlation with unexpected market volatility generate lower expected return.

We examine if the strong negative intertemporal relation between expected returns and market volatility risk is carried out to the cross-sectional relation as well. We conjecture that since there is a strong relation between expected returns and unexpected news in market volatility in stacked time-series and

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[16] To be consistent with the page length requirement of Management Science, in the online supplement, we present results from testing whether stocks that have higher correlation with $(RV^m - IV^m)$ yield lower expected return.

pooled panel regressions, the strong negative relation should appear in the cross-section of expected returns and unexpected news in firm-level volatility. Specifically, we test whether investors want to hedge against unexpected news in total volatility of individual stocks defined as the difference between realized volatility and average implied volatility of individual stocks (RVol-IVol). We investigate the presence and significance of a negative relation between expected stock returns and high covariance with innovations in firm-level volatility. Put differently, we examine whether individual stocks that have higher correlation with (RVol-IVol) would generate lower expected return.

To test this hypothesis, we sort all optionable NYSE stocks into quintile portfolios based on their firm-level volatility risk (RVol-IVol) in the previous month. As shown in Panel C of Table 8, for the value-weighted portfolios, we find a negative and economically significant average return difference on (RVol-IVol) quintile portfolios (in the range of 60 to 70 basis points per month). These average return differences are also statistically significant. For the equal-weighted portfolios, as presented in the second half of Panel C of Table 8, the relation between volatility risk and expected stock returns is also negative and 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 60 basis points per month with the statistic of −2.5 to −2.8. These average return differences from the value-weighted and equal-weighted portfolios of volatility risk are very similar to those obtained from the long-short portfolios of PC2 (Table 5, Panel B).

C. *An Interpretation of the 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, Richardson, and Whitelaw (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 D of Table 8, 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 1.0% to 1.5% per month that are highly significant. The t-statistics of average raw, abnormal, and risk-adjusted 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. These average return differences are very similar to those obtained from the long-short portfolios of PC3 as presented in Panel C of Table 5.

7. 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 AHXZ (2006) who use one-month lagged realized volatility to proxy for expected volatility and find that high volatility portfolios generate unusually low returns. Since we are able to replicate AHXZ (2006) results in our sample, the failure of implied volatility based trading strategies is puzzling.

To further investigate the differences and interactions between alternative measures of total risk, we transform our three measures of volatility into three orthogonal principal components. We find that although long-short trading strategies based on the first principal component do not generate significant returns, trading strategies based on the second and the third principal components generate economically large and statistically significant return. 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, and skewness.

The analysis of the economic content of the principal components with significant impact on returns suggests that the second principal component is related to the realized-implied volatility spread. We, therefore, conjecture that the second principal component is a proxy for volatility risk. The third principal component is related to the call-put implied volatility spread. Our conjecture is that the third principal component reflects investors' expectation about the future price increase of the underlying stock.

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Table 1. Portfolios sorted on realized volatility

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. Quintile 1 (5) denotes the portfolio of stocks with the lowest (highest) volatilities. The average monthly returns on quintile portfolios are reported in columns labeled “R”. 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 table. Size is the average market capitalization and B/M is the average book-to-market ratio for firms within the quintile portfolios. Call (put) volatility is the volatility implied by the call (put) option prices at the end of the previous month. 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 February 1996 to January 2005 period.

Panel A: All stocks

Quintile	R	Alpha	Realized Volatility	Market Share	Size	B/M
1	0.009	0.000	0.213	0.410	4,265	0.715
2	0.009	0.000	0.353	0.336	3,485	0.670
3	0.010	0.001	0.499	0.159	1,712	0.684
4	0.007	-0.003	0.712	0.072	790	0.701
5	-0.003	-0.015	1.340	0.024	269	0.808
5-1	-0.011	-0.015				
t-stat	-1.0	-2.8				

Panel B: Optionable stocks

Quintile	R	Alpha	Realized Volatility	Call Implied Volatility	Put Implied Volatility	Market Share	Size	B/M
1	0.008	0.000	0.226	0.304	0.310	0.408	9,932	0.540
2	0.009	0.000	0.352	0.401	0.406	0.342	7,360	0.503
3	0.010	0.001	0.498	0.524	0.531	0.160	3,871	0.478
4	0.006	-0.003	0.707	0.659	0.666	0.070	1,978	0.434
5	-0.003	-0.016	1.155	0.789	0.798	0.021	1,016	0.425
5-1	-0.012	-0.016						
t-stat	-1.0	-2.4						

Table 2. Portfolios sorted on implied volatility

Value-weighted quintile portfolios are formed every month by sorting stocks based on implied volatility from call and put 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 columns labeled "R". 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 table. Size is the average market capitalization and B/M is the average book-to-market ratio for firms within the quintile portfolios. Total volatility is the standard deviation of daily returns over the previous month. 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 February 1996 to January 2005 period.

Panel A: Call implied volatility

Quintile	R	Alpha	Realized Volatility	Call Volatility	Put Volatility	Market Share	Size	B/M
1	0.007	-0.002	0.266	0.270	0.269	0.456	17,602	0.502
2	0.011	0.002	0.345	0.357	0.362	0.285	11,019	0.502
3	0.012	0.004	0.439	0.455	0.461	0.148	5,837	0.490
4	0.007	0.000	0.580	0.589	0.596	0.078	3,146	0.446
5	0.002	-0.004	0.799	0.806	0.825	0.033	1,354	0.375
5-1	0.000	-0.001						
t-stat.	0.0	-0.2						

Panel B: Put implied volatility

Quintile	R	Alpha	Realized Volatility	Call Volatility	Put Volatility	Market Share	Size	B/M
1	0.006	-0.001	0.266	0.261	0.277	0.448	15,449	0.516
2	0.011	0.002	0.346	0.355	0.364	0.286	9,814	0.511
3	0.012	0.004	0.439	0.454	0.462	0.151	5,305	0.501
4	0.008	-0.001	0.578	0.587	0.597	0.080	2,873	0.458
5	0.005	-0.007	0.796	0.816	0.814	0.035	1,257	0.382
5-1	-0.005	-0.006						
t-stat.	-0.3	-0.8						

Table 3. Correlations between principal components and volatilities

The sample period is February 1996 to January 2005. 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. PC1 is the first principal component of volatilities. PC2 is the second principal component of volatilities. PC3 is the third principal component of volatilities. The principal components are estimated separately for each of 108 months.

	PC1	PC2	PC3	Realized Vol.	Call Vol.	Put Vol.
PC1	1					
PC2	0	1				
PC3	0	0	1			
Realized volatility	0.764	0.414	0.006	1		
Call volatility	0.854	-0.190	0.112	0.775	1	
Put volatility	0.854	-0.183	-0.118	0.777	0.969	1

Table 4. Portfolios sorted on principal components

Quintile portfolios are formed every month by sorting stocks based on principal components of realized and call and put implied volatilities, 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. PC1 is the first principal component of volatilities. PC2 is the second principal component of volatilities. PC3 is the third principal component of volatilities. Quintile 1 (5) denotes the portfolio of stocks with the lowest (highest) value of the principal component. 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 twenty-five benchmark portfolios formed based on market value of equity (ME) and book-to-market of equity. 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/AMEX/NASDAQ stocks with available data and covers February 1996 to January 2005 period.

Panel A: PC1

Quintile	R	Alpha	Market Share	Size	B/M	Realized Vol.	Call IV	Put IV
1	0.007	-0.001	0.440	17,722	0.496	0.244	0.268	0.275
2	0.010	0.001	0.289	11,635	0.496	0.334	0.357	0.365
3	0.013	0.004	0.155	6,335	0.490	0.433	0.455	0.463
4	0.008	0.001	0.081	3,430	0.433	0.571	0.590	0.598
5	0.003	-0.005	0.036	1,555	0.368	0.854	0.807	0.815
5-1	-0.004	-0.005						
t-stat	-0.3	-0.7						

Panel B: PC2

Quintile	R	Alpha	Market Share	Size	B/M	Realized Vol.	Call IV	Put IV
1	0.014	0.004	0.048	1,978	0.454	0.464	0.662	0.668
2	0.015	0.006	0.153	6,317	0.467	0.408	0.484	0.491
3	0.009	0.001	0.280	11,386	0.460	0.399	0.421	0.428
4	0.007	0.000	0.331	13,396	0.460	0.437	0.402	0.410
5	0.005	-0.003	0.188	7,632	0.442	0.727	0.507	0.518
5-1	-0.009	-0.008						
t-stat	-1.9	-2.0						

Panel C: PC3

Quintile	R	Alpha	Market Share	Size	B/M	Realized Vol.	Call IV	Put IV
1	0.002	-0.008	0.089	3,649	0.491	0.537	0.519	0.587
2	0.006	-0.002	0.215	8,664	0.446	0.458	0.456	0.477
3	0.010	0.003	0.328	13,336	0.430	0.438	0.443	0.450
4	0.010	0.002	0.266	10,907	0.438	0.458	0.470	0.464
5	0.014	0.005	0.101	4,146	0.479	0.545	0.588	0.537
5-1	0.012	0.013						
t-stat	3.8	3.7						

Table 5. Portfolios sorted on principal components: NYSE stocks

Quintile portfolios are formed every month by sorting stocks based on principal components of realized and call and put implied volatilities, 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. PC1 is the first principal component of volatilities. PC2 is the second principal component of volatilities. PC3 is the third principal component of volatilities. Quintile 1 (5) denotes the portfolio of stocks with the lowest (highest) value of the principal component. 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 twenty-five benchmark portfolios formed based on market value of equity (ME) and book-to-market of equity. 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 February 1996 to January 2005 period.

Panel A: PC1

	Value-weighted			Equal-weighted			Characteristics		
Quintile	R	AR	Alpha	R	AR	Alpha	Market Share	Size	B/M
1	0.005	-0.004	-0.003	0.008	-0.002	-0.002	0.352	19,194	0.506
2	0.010	0.001	0.002	0.011	0.000	-0.001	0.291	15,544	0.486
3	0.011	0.001	0.000	0.012	0.000	-0.001	0.185	9,938	0.512
4	0.011	0.002	0.001	0.014	0.003	0.000	0.110	6,018	0.534
5	0.005	-0.003	-0.005	0.011	0.001	-0.005	0.061	3,466	0.577
5-1	0.000	0.001	-0.002	0.003	0.003	-0.003			
t-stat	0.0	0.1	-0.6	0.5	0.6	-0.9			

Panel B: PC2

	Value-weighted			Equal-weighted			Characteristics		
Quintile	R	AR	Alpha	R	AR	Alpha	Market Share	Size	B/M
1	0.015	0.004	0.003	0.015	0.004	0.000	0.069	3,801	0.579
2	0.012	0.003	0.002	0.012	0.001	-0.001	0.170	9,327	0.518
3	0.008	-0.001	0.000	0.011	0.000	-0.001	0.258	13,982	0.499
4	0.008	-0.002	0.000	0.010	-0.001	-0.001	0.293	15,824	0.497
5	0.007	-0.002	-0.002	0.008	-0.003	-0.005	0.210	11,297	0.521
5-1	-0.007	-0.006	-0.005	-0.007	-0.006	-0.005			
t-stat	-2.4	-2.0	-1.9	-2.7	-2.7	-2.1			

Panel C: PC3

	Value-weighted			Equal-weighted			Characteristics		
Quintile	R	AR	Alpha	R	AR	Alpha	Market Share	Size	B/M
1	0.004	-0.005	-0.006	0.006	-0.005	-0.008	0.109	5,837	0.581
2	0.006	-0.004	-0.004	0.009	-0.002	-0.003	0.217	11,623	0.502
3	0.009	0.001	0.002	0.010	0.000	-0.002	0.289	15,738	0.481
4	0.009	0.000	0.000	0.012	0.001	-0.001	0.256	14,018	0.487
5	0.016	0.006	0.006	0.020	0.008	0.006	0.129	6,996	0.563
5-1	0.012	0.011	0.012	0.014	0.013	0.014			
t-stat	4.1	3.8	3.9	7.7	7.7	8.9			

Table 6. Principal component arbitrage portfolios with controls for other cross-sectional effects

Each month, all NYSE stocks with available data are first sorted based on firm characteristic (size, illiquidity, bid-ask spread, AFD, and PIN) and then, within each characteristic quintile the stocks are sorted based on the principal component. The five principal component quintile portfolios are then averaged over each of the five characteristic portfolios. Hence, they represent principal component quintile portfolios controlling for the characteristic. Each row reports the average monthly returns on an arbitrage portfolio with a long position in PC quintile portfolio 5 and a short position in PC 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 twenty-five benchmark portfolios formed based on market value of equity (ME) and book-to-market of equity. The Jensen’s alphas with respect to the Fama-French (1993) three-factor model are reported in columns labeled “Alpha”. The principal components of realized and call and put implied volatilities are 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. PC2 is the second principal component of volatilities. PC3 is the third principal component of volatilities. Size is the market capitalization of the stock. Illiquidity is Amihud’s measure of illiquidity. Spread 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. The reported t-statistics are Newey-West (1987) adjusted. The sample consists of all NYSE stocks with available data and covers February 1996 to January 2005 period.

Panel A: PC2

	Value-weighted						Equal-weighted					
	R	t-stat	AR	t-stat	Alpha	t-stat	R	t-stat	AR	t-stat	Alpha	t-stat
Size	-0.006*	-2.4	-0.006*	-2.3	-0.005*	-2.0	-0.007**	-2.8	-0.006**	-2.7	-0.006*	-2.3
Book-to-market	-0.007**	-3.2	-0.007**	-3.3	-0.006**	-2.7	-0.007**	-3.0	-0.007**	-3.3	-0.005*	-2.3
Illiquidity	-0.008**	-3.0	-0.008**	-3.2	-0.007*	-2.6	-0.007**	-3.0	-0.007**	-3.0	-0.006*	-2.5
Spread	-0.010**	-3.7	-0.010**	-3.9	-0.009**	-3.0	-0.006**	-2.7	-0.006**	-2.7	-0.005*	-2.2
AFD	-0.009**	-3.6	-0.008**	-3.5	-0.008**	-3.4	-0.009**	-3.4	-0.008**	-3.4	-0.007**	-2.8
PIN	-0.006	-1.7	-0.005	-1.6	-0.003	-1.2	-0.007**	-2.9	-0.007**	-2.8	-0.006*	-2.5
Skewness	-0.008**	-2.4	-0.006*	-2.0	-0.005	-1.8	-0.008**	-2.8	-0.007**	-2.9	-0.005*	-2.2

Panel B: PC3

	Value-weighted						Equal-weighted					
	R	t-stat	AR	t-stat	Alpha	t-stat	R	t-stat	AR	t-stat	Alpha	t-stat
Size	0.014**	6.4	0.014**	6.1	0.014**	6.4	0.015**	6.8	0.014**	6.7	0.015**	6.8
Book-to-market	0.012**	4.2	0.012**	4.3	0.012**	4.0	0.015**	7.5	0.014**	7.2	0.015**	8.4
Illiquidity	0.015**	6.3	0.014**	6.4	0.015**	6.1	0.014**	7.0	0.014**	7.0	0.014**	7.3
Spread	0.013**	4.1	0.013**	3.9	0.014**	4.2	0.014**	7.3	0.013**	7.2	0.014**	8.5
AFD	0.013**	4.8	0.012**	4.9	0.014**	5.0	0.014**	7.1	0.013**	7.1	0.014**	8.0
PIN	0.017**	6.8	0.015**	6.7	0.017**	6.1	0.016**	8.0	0.015**	7.6	0.016**	8.1
Skewness	0.011**	5.0	0.010**	4.8	0.012**	4.8	0.014**	7.4	0.013**	7.1	0.013**	8.0

Table 7. Fama-MacBeth regressions of individual NYSE stock returns

Each month, we estimate a cross-sectional regression of individual stock returns. PC1 is the first principal component of volatilities. PC2 is the second principal component of volatilities. PC3 is the third principal component of volatilities. The principal components of realized and call and put implied volatilities are 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. MVE is the market capitalization (size) of the stock. B/M is the book-to-market ratio of the firm's equity. Illiquidity is Amihud's measure of illiquidity. 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. The reported coefficients are the time-series averages of the coefficients from monthly regressions. The reported t-statistics are based on the time-series standard deviation of regression coefficients and Newey-West (1987) adjusted. The sample consists of all NYSE stocks with available data and covers February 1996 to January 2005 period.

	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	0.011	1.8	0.021*	2.2	0.029	1.9
PC1	0.000	0.1	-0.001	-0.2	-0.002	-0.5
PC2	-0.007**	-3.5	-0.006**	-3.3	-0.005*	-2.6
PC3	0.034**	6.7	0.033**	6.7	0.042**	7.4
Ln(MVE)			-0.001	-1.3	-0.002	-1.3
Ln(B/M)			0.001	0.9	0.001	0.9
Illiquidity					-0.119	-1.2
AFD					-0.018**	-4.9
PIN					-0.047	-1.7
Skewness					-0.001	-1.1
Observations	108		108		83	

Table 8. Principal Components, Realized-Implied Volatility Spread, and Call-Put Implied Volatility Spread

Quintile portfolios are formed every month by sorting stocks based on principal components of realized and call and put implied volatilities, estimated over the previous month. Realized volatility (RVol) is the standard deviation of daily returns over the previous month. Call volatility (CVol) is the volatility implied by the call prices at the end of the previous month. Put volatility (PVol) is the volatility implied by the put prices at the end of the previous month. IVol is the implied volatility calculated from both call and put prices at the end of the previous month. PC1 is the first principal component of volatilities. PC2 is the second principal component of volatilities. PC3 is the third principal component of volatilities. Quintile 1 (5) denotes the portfolio of stocks with the lowest (highest) value of the principal component. 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 twenty-five benchmark portfolios formed based on market value of equity (ME) and book-to-market of equity. 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 difference between quintile portfolios 5 and 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 February 1996 to January 2005 period.

Panel A: Distribution of (RVol-IVol) and (CVol-PVol) across PC quintiles

	PC1 Quintiles		PC2 Quintiles		PC3 Quintiles	
Quintile	CVol-PVol	RVol-IVol	CVol-PVol	RVol-IVol	CVol-PVol	RVol-IVol
1	-0.007	-0.028	-0.007	-0.165	-0.055	-0.021
2	-0.006	-0.026	-0.006	-0.071	-0.017	-0.016
3	-0.006	-0.026	-0.006	-0.026	-0.006	-0.015
4	-0.007	-0.023	-0.007	0.019	0.005	-0.017
5	-0.009	0.010	-0.009	0.152	0.038	-0.024
5-1	-0.002	0.038	-0.002	0.317	0.093	-0.003
t-stat	-1.2	6.3	-1.4	18.3	11.2	-0.8

Panel B: Correlation matrix

	PC1	PC2	PC3	CVol - PVol
CVol – PVol	-0.030	-0.003	0.937	1
RVol – IVol	0.153	0.896	-0.001	-0.021

Panel C: Portfolio returns by realized-implied volatility spread (RVol-IVol) quintiles

	Value-weighted			Equal-weighted			Characteristics		
Quintile	R	AR	Alpha	R	AR	Alpha	Market Share	Size	B/M
1	0.013	0.004	0.003	0.015	0.003	0.001	0.082	3,806	0.597
2	0.012	0.003	0.003	0.013	0.002	0.000	0.192	8,893	0.540
3	0.008	0.000	0.000	0.011	0.000	-0.001	0.268	12,223	0.521
4	0.008	-0.001	-0.001	0.011	-0.001	-0.002	0.275	12,422	0.521
5	0.006	-0.003	-0.004	0.008	-0.003	-0.005	0.183	8,229	0.548
5-1	-0.007	-0.006	-0.006	-0.006	-0.006	-0.006			
t-stat	-2.9	-2.6	-2.2	-2.8	-2.7	-2.5			

Panel D: Portfolio returns by call-put implied volatility spread (CVol-PVol) quintiles

	Value-weighted			Equal-weighted			Characteristics		
Quintile	R	AR	Alpha	R	AR	Alpha	Market Share	Size	B/M
1	0.003	-0.006	-0.007	0.005	-0.006	-0.009	0.107	5,872	0.594
2	0.006	-0.003	-0.003	0.010	-0.001	-0.003	0.219	11,970	0.503
3	0.008	-0.001	0.001	0.009	-0.001	-0.003	0.291	16,076	0.471
4	0.010	0.001	0.001	0.012	0.002	0.000	0.251	14,050	0.483
5	0.014	0.004	0.004	0.019	0.008	0.006	0.132	7,364	0.556
5-1	0.010	0.010	0.011	0.014	0.014	0.015			
t-stat	4.2	3.9	4.5	7.9	8.5	8.6			