Variation in Option Implied Volatility Spread and Future Stock Returns

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Abstract

Equity option markets exhibit intense trading activity. We use the variability of option implied volatility spread as a proxy for the impounding of new information and changes in the interpretation of existing information, into option prices. Over the 2006 – 2016 period, the predictive power of option implied volatility spread for future stock returns is significantly greater when implied volatility spread has been more variable in the past. Our results are statistically and economically significant and robust in both univariate and multivariate settings.

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1. INTRODUCTION

Understanding how information flows between option and stock markets continues to be an important topic in finance. Fischer Black (1975) was an early proponent of the idea that traders with private information might prefer to transact in option markets ahead of stock markets. Equity option markets exhibit intense trading activity, and deviation in the call-put parity (as measured by the option implied volatility spread) is shown in the literature to be robust predictor of the underlying stock's returns. In this study, we use the volatility of call-put deviations (computed as the standard deviation of option implied volatility spread) as a proxy for impounding new information and changes in the interpretation of existing information, into option prices. Over the 2006 – 2016 period, the predictive power of option implied volatility spread for future stock returns is significantly greater when implied volatility spread has been more variable in the recent past.

Early support for Black's assertion is found by Manaster & Rendelman (1982) who show that option markets may provide a preferred outlet for informed investors. They find that closing prices of listed call options contain information about equilibrium stock prices that is not contained in the closing prices of underlying stocks. They offer two potential explanations for their finding. The simplest is that closing option and stock transactions do not always take place at the same time. The alternative is that closing option prices reflect fundamental information about the equilibrium values of underlying stocks that is not contained in closing stock prices. To test this they use the Black & Scholes (1973) option pricing model to calculate implied stock prices to compare with observed stock prices 24 hours later. They wait 24 hours to allow time for the nonsynchronous data effect to be absorbed into observed stock prices. However, their analysis reveals that the implied prices still contain information regarding equilibrium stock prices that is not fully reflected in observed stock prices a day later. Thus, they conclude that option prices do reflect information not already present in stock prices.

Stephan & Whaley (1990) present evidence that informed investors prefer to transact in option markets, while Sheikh & Ronn (1994) examine option return patterns, and argue that differences between these and equity market returns are evidence of information based trades in options. In particular, they find that option returns contain systematic patterns even after adjusting for patterns in the means and variances of the underlying assets. This is consistent with the hypothesis that informed trading in options can make the options market informative about the value of the underlying asset. Easley, O'Hara, & Srinivas (1998) investigate the informational role of transactions volume in options markets by developing and testing an asymmetric information model in which informed traders may trade in option or equity markets. Their main empirical result supports the notion that options markets are an important venue for information based trading.

Stock return predictability by implied volatility has been empirically examined in number of studies including Diavatopoulos, Doran, & Peterson (2008), Bali & Hovakimian (2009), Zhang, Zhao & Xing (2010), Jin, Livnat & Zhang (2012), Diavatopoulos et al. (2012), Doran, Fodor & Jiang (2013) and DeLisle et al. (2018). A consistent theme in these studies is that implied volatility innovations, which are forward looking, have predictive power for future stock returns and thus reflects investor beliefs about future stock valuations. However, in this paper, we focus on the findings of Cremers & Weinbaum (2010) and Doran & Krieger (2010): deviations in call-put parity have very strong predictive power over future stock returns. Cremers & Weinbaum show deviations in call-put parity can be expressed as the option implied volatility spread between an at-the-money call and an at-the-money (ATM) put. Cremers & Weinbaum show this implied volatility spread is strongly positively related with the underlying stocks' future returns. Doran and Krieger find the implied volatility spread subsumes many other option-related measures with respect to stock return predictability. However, no study to date examines whether or not the variation of the implied volatility spread conveys any information about the underlying stocks' future returns.

Our hypothesis is that the second moment of the implied volatility spread also contains information pertinent to future stock returns; firms with stagnant implied volatility spreads contribute less to the profitability of a portfolio than those with more volatile implied volatility spreads. Stated differently, we conjecture that stocks with more variance in their implied volatility spreads will have more extreme future returns than those with low variance, and thus a long-short strategy using implied volatility spread will be the more profitable for firms with high variance of implied volatility spread. Consider a stock whose implied volatility spread remains consistently high (low) with very low variance in the spread. The high (low) implied volatility spread indicates that the stock is undervalued (overvalued). The low variance in the spread indicates that the stock remains undervalued (overvalued) for a very long time, with its price never converging to fundamental value. Thus, the stock would not contribute much "alpha" to a portfolio long (short) this stock. Our hypothesis says nothing about the variability of the implied volatility spread as a stand-alone profitability signal. Rather, we hypothesize that using the conjunction of both the level and variance of the implied volatility spread will result in better portfolio performance than using the level alone.

We first use portfolio sorting to determine the impact implied volatility spread variability has on future stock returns at daily, weekly, and monthly rebalancing frequencies. All the results consistently show that forming long-short portfolios based on the level of implied volatility spread (long high spread and short low spread) conditioned on high variability of implied volatility spread outperforms long-short portfolios conditioned on low variability of implied volatility spread. For example, at the monthly rebalancing frequency, a long-short portfolio using the level implied volatility spread (long in high spread and short in low spread stocks) for low implied volatility spread *variability* stocks earns an average monthly return of 0.199%. However, a similar strategy for high implied volatility spread *variability* stocks earns an average monthly return of 1.796%, nearly nine times larger than its low spread variability counterpart.

Fama and MacBeth (1973) regressions controlling for firm size, momentum, and liquidity are consistent with the portfolio sorting results; the variability of the implied volatility spread enhances the stock return predictability of the implied volatility spread level. Additionally, we risk-adjust the sorted portfolio returns using the Fama and French (2015) five-factor model and again find results consistent with our hypothesis. For example, a long-short portfolio based on implied volatility spread that is conditional on high implied spread variability earns a monthly alpha almost 5 times larger than a long-short portfolio conditioned on low implied volatility spread variability (2.267% versus 0.437%, respectively). Thus, the overall evidence supports our hypothesis that the variability of the implied volatility spread contains information about future stock returns. Higher variance in the implied volatility spread improves the ability of the implied volatility spread level to predict future stock returns.

Our study is related to Moreira & Muir (2017) that show that, across a variety of anomalies involving longing and shorting based on the level of a particular firm characteristic, weighting the long and the short legs of the portfolio by the inverse of that particular leg's return volatility (e.g. giving higher weight to the leg with lower portfolio return volatility) yields higher performance than equal weighting the long and short legs. However, our paper differs from Moreira & Muir (2017) in a significant way. We use the volatility of the firm characteristic – specifically, the volatility of the implied volatility spread – as an additional informative signal to help us identify candidate firms that would be included in the long and short leg of the portfolio and improve the performance of the strategy. Unlike Moreira & Muir, a long-short portfolio based on level of implied volatility spread is weighted by the variability of the implied volatility spread (i.e. the variability of firm-specific characteristic) and not the inverse of the variance of the portfolio return.

Overall, we contribute to the literature by showing that the firm-specific variability of the implied volatility spread contains relevant information that is useful in forecasting stock returns when used in combination with the implied volatility spread level.

2. DATA AND VARIABLE DEFINITIONS

2.1 Data

The sample period studied is from January, 2006 to December, 2016. We collect data on option prices, strike prices, exercise dates, option trading volume, open interest, and implied volatilities from OptionMetrics. Stock prices, number of outstanding shares, stock trading volume, and stock returns data are taken from CRSP for the construction of control measures.

2.2 Variable Definitions

All measures using implied volatility are calculated using all options with 90 or fewer days to expiration. Following Cremers & Weinbaum (2010), CPIV is the open interest-weighted call implied volatility less open interest weighted put implied volatility. CPIV STD is the standard deviation of CPIV over the past 20 days. IV is the open interest-weighted implied volatility. ME is stock price multiplied by the number of shares outstanding at the end of the measurement period and is reported in billions. Return is the daily, weekly, or monthly return on the day, week, or month, respectively, following CPIV measurement. Reversal is return in the calendar month prior to CPIV measurement. Momentum is the cumulative return in calendar months in brackets relative to the date of CPIV measurement. Turnover is monthly volume divided by the number of shares outttanding over calendar months prior to CPIV measurement with months designated in brackets. Illiquidity is the illiquidity measure of Amihud (2002), the absolute value of the return divided by the dollar trading volume averaged over calendar days prior to CPIV measurement, with days designated in brackets.

2.3 Descriptive Statistics

We first present descriptive statistics (particularly, equal weighted averages) of the main variables used in the empirical analysis after dividing the sample into quintiles based on the standard deviation of implied volatility spread (CPIV STD) and market cap. These results are reported in Panels A and B of Table 1, respectively. Panel A shows that the standard deviation of implied volatility spread (CPIV STD) increases monotonically (by construction) from an average of 0.023 in the first CPIV STD quintile to 0.197 in the fifth CPIV STD quintile, an increase of more than eight fold. This result suggest that CPIV is highly variable for the firms in our sample. The table also shows that the level of CPIV decreases from an average of -0.034 in the first CPIV STD quintile to an average of -0.065 in the fifth CPIV STD quintile. Further, Panel A shows that IV, reversal, momentum, turnover, and illiquidity increase, but firm size decreases, nearly monotonically as we move from low to high CPIV STD quintile.

In Panel B, we report equal weighted averages of firm characteristics used in the main empirical analysis after dividing the sample into quintiles by firm size. This panel shows that CPIV STD decreases with firm size, which is consistent with the result reported in Panel B. Further, the results show that CPIV increases with firm size but IV, illiquidity, and turnover decrease with firm size. Firm size seems to have an inverse-U relation with momentum and reversal.

3. EMPIRICAL RESULTS

3.1 Portfolio Sorts

We start our empirical analysis by confirming the Cremers & Weinbaum finding that the high option implied volatility spread (CPIV) stocks are associated with higher returns in our sample. We present results from an equal weighted univariate quintile sort in the first column of Panel A of Table 2. The table show that the one-day, five-day, and twenty-day average returns for the lowest CIPV quintile are, respectively, -2.9, -1.9, and

12.8 basis points (or bps) and increase monotonically to 9.2, 26.2, and 77.9 bps for the highest CPIV quintile. Further, we find that a trading strategy goes long in high CPIV quintile firms and short in low CPIV quintile firm produces an economically large and statistically significant average return. Specifically, this strategy generates a one-day, five-day, and twenty-day average returns of 12.1 bps (p-value<0.01), 27.4 bps (p-value<0.01), and 65.1 bps (p-value<0.01) respectively. After confirming that the option implied volatility spread (CPIV) is positively correlated with returns in our sample, we proceed in our analysis by showing that this correlation is substantially larger for highly volatile CPIV firms using bivariate sorts.

[Insert Table 2 here]

In Panel A of Table 2, we report equal weighted average returns from a bivariate dependent sort, where we sort stocks into quintiles first by the historical standard deviation of option implied volatility spread (CPIV STD) and then, within each of these quintiles, we sort stocks into quintiles by CIPV. In the last raw, we report the high-minus-low CPIV returns for each of the five CPIV STD quintile portfolios. The results show that the average returns from the high-minus-low CPIV strategy nearly monotonically increase as we move from low CPIV STD portfolios to high CPIV STD portfolios.

Specifically, for one-day average returns, we find that the high-minus-low CPIV strategy in the highest CPIV STD quintile portfolio is 3.6 times larger than the high-minus-low CPIV strategy in the lowest CPIV STD quintile portfolio (6.9 vs. 24.8 bps). Furthermore, the high-minus-low CPIV strategy in the highest CPIV STD quintile portfolio is more than twice larger than the high-minus-low CPIV strategy for the whole sample (24.8 vs. 12.1 bps.) The result for five-day average returns are even more pronounced. The table shows that the high-minus-low CPIV strategy for the highest CPIV STD quintile portfolio is more than 5.4 times larger than the high-minus-low CPIV strategy for the lowest CPIV STD quintile portfolio (13.6 vs. 74.1 bps). Furthermore, it shows that the high-minus-low CPIV strategy for the highest CPIV STD quintile portfolio is more than 2.7 times larger than the high-minus-low CPIV strategy for the whole sample (27.4 vs. 74.1 bps). Finally, we find even stronger results for the twenty-day (approximately one month) average returns. The high-minus-low CPIV strategy for the lowest CPIV STD quintile portfolio is more than nine times larger than the high-minus-low CPIV strategy for the lowest CPIV STD quintile portfolio (179.6 vs.19.9 bps), and is more than 2.8 times larger than the high-minus-low CPIV strategy for the whole sample (179.6 vs. 65.1 bps.)

Panel B of Table 2 presents equal weighted returns from using independent bivariate sorts. We again find that the high-minus-low CPIV strategy monotonically increases as we move from low CPIV STD portfolios to high CPIV STD portfolios. These results confirm the main findings from using dependent bivariate sort in Panel A. Taken together, the results from Table 2 show that the predictive power of option implied volatility spread for future stock returns is significantly greater when implied volatility spread has been more variable in the recent past.

Our main tests thus far show that the CPIV effect is pronounced within the highest CPIV STD quintile firms. Next, we study the effect of CPIV STD on the universe of stocks. Similar to the approach we used above, we first perform univariate sorts by CPIV STD and present the results in the first column of Panel A of Table 3.

[Insert Table 3 here]

We find that high CPIV STD firms underperform low CPIV STD firms. An investment strategy that goes long in high CPIV STD firms and short in low CPIV STD firms generates a one-day average return of -1.1 bps (t-stat = 1.62), a five day average return of -5.3 bps (t-stat = 3.66), and a twenty-day average return of -18.8 bps (t-stat = 6.73). Additionally, we perform dependent sorts, first by CPIV and then by CPIV STD. We find that high CPIV STD firms underperform low CPIV STD firms for the lowest CPIV quintile, but high CPIV STD firms outperform low CPIV STD firms for the highest CPIV quintile. For example, Panel A of Table 3 shows that the average one-day return for the lowest CPIV STD firms within the *lowest* CPIV quintile is -0.1 bps and the average one-day return for the highest CPIV STD firms within the *lowest* CPIV quintile is -9.1 bps. However, the average one-day return for the lowest CPIV STD firms within the *highest* CPIV quintile is 7.3 bps and the average one-day return for the highest CPIV STD firms within the *highest* CPIV quintile is 12.1 bps. This finding holds for five-day and twenty-day average returns and for dependent and independent sorts. This result suggest that there is some interaction effect going on between CPIV and CPIV STD. We study this further using a Fama-MacBeth Regression approach with interaction terms between CPIV and CPIV STD.

3.2 Fama-MacBeth Regression Analyses

Given the portfolio sorts yield large differences in the raw returns, we turn to Fama-MacBeth regressions to see if there is an interactive effect between CPIV STD and level that affects future returns. Using this method allows for controlling for multiple variables at the same time without an extremely large sample size required by sorting on many variable dimensions. Since daily returns tend to be extremely noisy in this type of analysis, we focus on monthly returns. We regress monthly returns at the end of month t on variables calculated at the end of month t-1. The independent variables are CPIV (the open interest weighted call implied volatility less open interest weighted put implied volatility), CPIV STD (the standard deviation of CPIV over the past 20 days), High STD (an interaction variable which takes a value of CPIV if is in the highest quintile for CPIV STD), IV (open interest weighted implied volatility), Reversal (return in the calendar month prior to CPIV measurement), Momentum [-13,-2] (return in calendar months -13 through -2 relative to the date of CPIV measurement), Turnover[-1] (turnover from the month prior to CPIV measurement), and Illiquidity[-22,-1] (the illiquidity measure of Amihud (2002) over the 21 calendar days prior to CPIV measurement). All measures using implied volatility are calculated using all options with 90 or fewer days to expiration.

[Insert Table 4 here]

Table 4 shows the results from the Fama-MacBeth regressions. Model 1 omits CPIV STD and High STD. CPIV is highly significant (p-value<0.01) and positive, indicating that high (low) CPIV is predictive of high (low) returns. In Model 2, CPIV STD is included in the estimation. In this model, CPIV remains highly significant, but CPIV STD by itself is not predictive of future returns. In Model 3, High STD is included. Both CPIV and High STD are statistically significant (p-value<0.05 and p-value<0.10, respectively), while CPIV STD remain statistically insignificant. High STD is also positive, which means that stocks with high CPIV STD and high (low) CPIV have higher (lower) returns than stocks not in the highest quintile of CPIV STD. These results are consistent with the notion that using both the level and volatility of CPIV can increase portfolio performance relative to just using the CPIV level.

3.3 Portfolio Regression Analyses

In order to test the ability of the CPIV STD to increase the risk-adjusted returns of CPIV portfolios, we regress portfolio returns on the Fama & French (2015) five-factor risk model and examine the portfolio alphas. First, we start with verifying the results of Cremers & Weinbaum (2010) and Doran & Krieger (2010) by sorting stocks into portfolios based on their CPIV. Table 5 shows the results of regressing the equally-weighted portfolio returns on the five-factor model. Panel A of Table 5 shows the results using daily returns. The portfolio alphas monotonically increase from -6 bps per day (p-value<0.01) to 6 bps per day (p-value<0.01). Thus, a portfolio long high CPIV stocks and short low CPIV stocks would yield a five-factor alpha of 12 bps per day, or 30% per year (based on a 250 trading-day year). This confirms CPIV's stock return predictability at a daily level. However, rebalancing portfolios at a daily frequency would most likely result in transaction costs that would subsume the alpha from this strategy.

[Insert Table 5 here]

Next, we rebalance the portfolios at a monthly frequency. Rebalancing on a monthly basis reduces the transaction costs to a more feasible level than daily rebalancing. Panel B of Table 5 shows that the five-factor alphas monotonically increase from -74.6 bps per month (p-value<0.01) in the low CPIV portfolio to 25.7 bps per month (p-value>0.10). This indicates that a portfolio long in high CPIV stocks and short in low CPIV stocks would, on average, earn an alpha of 100.3 bps per month, or 12.04% annually. These results again confirm the findings of Cremers & Weinbaum and Doran & Krieger; CPIV is a strong predictor of future stock returns, even when adjusting for risk.

We now investigate if using the CPIV STD can improve stock return predictability. We sort stocks sequentially quintiles first by CPIV STD and then by the CPIV level. The five-factor portfolio alphas are then estimated. Panel A of Table 6 shows the daily five-factor alphas from each of the twenty-five portfolios. In the low CPIV STD quintile, the high CPIV stocks have an alpha of 4.9 bps per day (p-value<0.01) and the low CPIV stocks have an alpha of -2.2 bps per day (p-value<0.01), with a difference between the two of 7.1 bps per day. While in the high CPIV STD quintile, stocks with high CPIV have an alpha of 10.5 bps per day (p-value<0.01) and stocks with low CPIV have an alpha of -14.1 bps per day (p-value<0.01), for a difference of 24.6 bps per day between the two. Thus, the CPIV long-short portfolio yields an alpha almost 3.5 times larger in the high CPIV STD group than in the low CPIV STD group. This evidence supports the hypothesis that CPIV adds additional information and predictability about future stock returns.

[Insert Table 6 here]

Again, daily rebalancing of portfolios can incur large transactions costs, so we repeat the daily analysis but using monthly rebalancing. Panel B of Table 6 shows the results from the estimations. In the low CPIV STD quintile, the high CPIV stocks have an alpha of 32.0 bps per day (p-value<0.05) and the low CPIV stocks have an alpha of -11.7 bps per month (p-value>0.10), with a difference between the two of 43.7 bps per month. However, in the high CPIV STD quintile, stocks with high CPIV have an alpha of 41.8 bps per month (p-value>0.10) and stocks with low CPIV have an alpha of -184.9 bps per month (p-value<0.01), for a difference of 226.7 bps per month between the two. Therefore, the

CPIV long-short portfolio yields an alpha almost 5 times larger in the high CPIV STD quintile than in the low CPIV STD quintile. Once again, these result support the hypothesis that not only the level, but also the volatility of CPIV is useful in predicting stock returns.

Sequential sorting ensures there is a similar number of stocks in each portfolio, but it could result in smaller variation of CPIV levels across CPIV quintiles. Therefore, for robustness purposes, we repeat the previous analyses using independent sorting of CPIV levels and CPIV STD. The results are reported in Panels C and D of Table 6 and are very similar to the sequential sorting results. Panel C shows that the CPIV long-short portfolio yields a daily alpha about 2.3 times larger in the high CPIV STD quintile than in the low CPIV STD quintile (19.3 bps in the high CPIV STD versus 8.5 bps in the low CPIV STD). Lastly, Panel D demonstrates that the CPIV long-short portfolio yields a monthly alpha over 7 times larger in the high CPIV STD quintile than in the low CPIV STD quintile (177.6 bps in the high CPIV STD versus 25.2 bps in the low CPIV STD). Taken altogether, there is strong evidence that CPIV STD is important variable in determining future stock returns. Stocks with low CPIV STD have a CPIV level that is not as informative about future returns than those with high CPIV STD. If an investor were to employ a strategy that longs high CPIV stocks and shorts low CPIV stocks in only stocks with high CPIV STD, they would yield an alpha approximately twice as large as just a simple long-short portfolio based just on CPIV level (2.26% for dependent sort or 1.77% for independent sort versus 1.003%, respectively).

4. CONCLUSION

In this study we use the variability of option implied volatility spread as a proxy for the impounding of new information and changes in the interpretation of existing information, into option prices. We find that the second moment of the implied volatility spread contains information pertinent to future stock returns; firms with stagnant implied volatility spreads contribute less to the profitability of a portfolio structured based on CPIV than those with more variance in implied volatility spreads.

Our findings suggest a portfolio strategy using the conjunction of both the level and variability of the implied volatility spread will result in better portfolio performance than using the level alone. A portfolio long both high implied volatility spread level and high implied volatility spread variability stocks and short low implied volatility spread level and high implied volatility spread variability earns an average monthly return of 1.796%, nearly nine times larger than its low spread variability counterpart.

Our results are statistically and economically significant and robust in both univariate and multivariate settings. Fama & MacBeth (1973) regressions controlling for firm size, momentum, and liquidity are consistent with the portfolio sorting results; the variability of the implied volatility spread enhances the stock return predictability of the implied volatility spread level. Additionally, we risk-adjust the sorted portfolio returns using the Fama & French (2015) five-factor model and again find results consistent with our hypothesis.

Collectively, the evidence in our study supports the hypothesis that the variability of implied volatility spread contains information about future stock returns. Higher variance in the implied volatility spread improves the ability of the implied volatility spread level to predict future stock returns. This implies investors using the level of implied volatility spread to construct portfolios should weight the stocks in the portfolio by the standard deviation of their implied volatility spread to improve both raw and risk-adjusted returns. Future research in this area includes investigating if this finding generalizes to the second moment of more option-related predictors of stock returns.

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Table 1: Descriptive Statistics

Table 1 presents descriptive statistics after dividing the sample into quintiles based on the standard deviation of CPIV (CPIV STD) over the past 20 days in Panel A and based on market equity (ME) in Panel B. CPIV is the open interest weighted call implied volatility less open interest weighted put implied volatility. IV is open interest weighted implied volatility. Return is the daily return on the day following CPIV measurement. Reversal is return in the calendar month prior to CPIV measurement. Momentum [-4,-2] is return in calendar months -4 through -2 relative to the date of CPIV measurement. Momentum [-7,-2] and Momentum [-13,-2] are return in months -7 through -2 and -13 through -2 respectively. Turnover is monthly turnover over calendar months prior to CPIV measurement with months designated in brackets. Illiquidity is the illiquidity measure of Amihud (2002) over calendar days prior to CPIV measurement with days designated in brackets. All measures using implied volatility are calculated using all options with 90 or fewer days to expiration. ME is in billions.

Panel A	Low CPIV STD Quintile	CPIV STD Quintile 2	CPIV STD Quintile 3	CPIV STD Quintile 4	High CPIV STD Quintile
CPIV	-0.034	-0.036	-0.040	-0.046	-0.065
CPIV STD	0.023	0.041	0.061	0.093	0.197
IV	0.326	0.394	0.454	0.529	0.673
ME	38.478	14.565	8.336	4.851	2.427
Return	0.000	0.000	0.000	0.000	0.000
Reversal	0.008	0.012	0.013	0.016	0.011
Momentum [-4,-2]	0.030	0.042	0.048	0.053	0.041
Momentum [-7,-2]	0.065	0.090	0.103	0.117	0.094
Momentum [-13,-2]	0.139	0.184	0.219	0.244	0.191
Turnover [-1]	2.262	2.975	3.393	3.698	3.946
Turnover [-3,-1]	2.291	2.993	3.389	3.663	3.826
Turnover [-6,-1]	2.302	2.991	3.359	3.606	3.734
Turnover [-12,-1]	2.312	2.977	3.312	3.513	3.596
Illiquidity [-22,-1]	0.027	0.069	0.129	0.241	0.676
Illiquidity [-66,-1]	0.077	0.092	0.161	0.258	0.657
Illiquidity [-125,-1]	0.088	0.130	0.202	0.300	0.690
Illiquidity [-250,-1]	0.123	0.169	0.281	0.436	0.809

Panel B	Low ME Quintile	ME Quintile 2	ME Quintile 3	ME Quintile 4	High ME Quintile
CPIV	-0.064	-0.042	-0.038	-0.036	-0.042
CPIV STD	0.146	0.096	0.077	0.058	0.038
IV	0.733	0.527	0.435	0.367	0.315
ME	0.539	1.630	3.842	9.501	53.132
Return	0.000	0.000	0.000	0.000	0.000
Reversal	0.003	0.016	0.016	0.014	0.012
Momentum [-4,-2]	0.027	0.052	0.052	0.044	0.038
Momentum [-7,-2]	0.070	0.116	0.109	0.094	0.079
Momentum [-13,-2]	0.155	0.247	0.220	0.191	0.162
Turnover [-1]	4.352	4.008	3.368	2.747	1.845
Turnover [-3,-1]	4.318	3.961	3.351	2.736	1.847
Turnover [-6,-1]	4.255	3.906	3.316	2.719	1.848
Turnover [-12,-1]	4.139	3.815	3.257	2.697	1.853
Illiquidity [-22,-1]	0.903	0.161	0.059	0.021	0.005
Illiquidity [-66,-1]	0.883	0.176	0.072	0.060	0.062
Illiquidity [-125,-1]	0.895	0.210	0.094	0.096	0.122
Illiquidity [-250,-1]	1.022	0.289	0.154	0.160	0.199

Table 2: Double Sorts on CPIV STD and CPIV

Table 2 presents one-day, five-day and twenty-day returns after dividing the sample into quintiles based on CPIV STD and CPIV. In Panel A firms are sorted each day based on CPIV STD and further within these quintiles based on CPIV. In Panel B firms are sorted independently into quintiles based on CPIV STD and CPIV. In Panel A returns are also presented after sorting firms into quintiles based only on CPIV. High-low differences across CPIV quintiles and associated t-statistics are also presented. CPIV is the open interest weighted call implied volatility less open interest weighted put implied volatility. CPIV STD is the standard deviation of CPIV over the past 20 days. CPIV and CPIV STD are calculated using all options with 90 or fewer days to expiration.

Panel A: Dependent Sorts

One-Day Return	All	Low CPIV STD Quintile	CPIV STD Quintile 2	CPIV STD Quintile 3	CPIV STD Quintile 4	High CPIV STD Quintile
Low CPIV Quintile	-0.029	0.010	0.016	-0.013	-0.035	-0.113
CPIV Quintile 2	0.019	0.018	0.023	0.012	0.018	0.013
CPIV Quintile 3	0.037	0.042	0.020	0.041	0.040	0.048
CPIV Quintile 4	0.053	0.052	0.046	0.038	0.059	0.066
High CPIV Quintile	0.092	0.080	0.062	0.086	0.097	0.135
High-Low	0.121	0.069	0.046	0.099	0.132	0.248
t-stat	(16.79)	(7.19)	(3.93)	(7.11)	(8.01)	(11.45)

Five-Day Return	All	Low CPIV STD Quintile	CPIV STD Quintile 2	CPIV STD Quintile 3	CPIV STD Quintile 4	High CPIV STD Quintile
Low CPIV Quintile	-0.012	0.101	0.106	0.047	0.017	-0.341
CPIV Quintile 2	0.137	0.160	0.161	0.129	0.116	0.149
CPIV Quintile 3	0.180	0.205	0.124	0.187	0.193	0.190
CPIV Quintile 4	0.217	0.225	0.173	0.193	0.261	0.264
High CPIV Quintile	0.262	0.237	0.174	0.209	0.234	0.400
High-Low	0.274	0.136	0.068	0.162	0.216	0.741
t-stat	(17.30)	(6.58)	(2.66)	(5.37)	(6.05)	(15.28)

Twenty-Day Return	All	Low CPIV STD Quintile	CPIV STD Quintile 2	CPIV STD Quintile 3	CPIV STD Quintile 4	High CPIV STD Quintile
Low CPIV Quintile	0.128	0.562	0.523	0.319	0.046	-0.704
CPIV Quintile 2	0.610	0.680	0.602	0.665	0.414	0.607
CPIV Quintile 3	0.712	0.785	0.617	0.773	0.643	0.738
CPIV Quintile 4	0.769	0.814	0.683	0.777	0.740	0.907
High CPIV Quintile	0.779	0.760	0.618	0.728	0.576	1.092
High-Low	0.651	0.199	0.095	0.409	0.531	1.796
t-stat	(21.29)	(5.03)	(1.93)	(6.94)	(7.69)	(19.26)

Panel B: Independent Sorts

One-Day Return	Low CPIV STD Quintile	CPIV STD Quintile 2	CPIV STD Quintile 3	CPIV STD Quintile 4	High CPIV STD Quintile
Low CPIV Quintile	0.029	0.034	-0.009	-0.029	-0.087
CPIV Quintile 2	0.030	0.022	0.007	0.010	0.024
CPIV Quintile 3	0.038	0.018	0.035	0.051	0.057
CPIV Quintile 4	0.044	0.037	0.057	0.060	0.081
High CPIV Quintile	0.074	0.063	0.074	0.095	0.126
High-Low	0.045	0.029	0.083	0.124	0.213
t-stat	(3.12)	(2.16)	(6.02)	(8.51)	(12.82)

Five-Day Return	Low CPIV STD Quintile	CPIV STD Quintile 2	CPIV STD Quintile 3	CPIV STD Quintile 4	High CPIV STD Quintile
Low CPIV Quintile	0.189	0.156	0.042	0.021	-0.208
CPIV Quintile 2	0.160	0.146	0.112	0.126	0.129
CPIV Quintile 3	0.201	0.114	0.181	0.216	0.206
CPIV Quintile 4	0.182	0.183	0.239	0.238	0.280
High CPIV Quintile	0.211	0.142	0.191	0.255	0.408
High-Low	0.022	-0.013	0.149	0.234	0.616
t-stat	(0.71)	(0.45)	(4.99)	(7.38)	(16.57)

Twenty-Day Return	Low CPIV STD Quintile	CPIV STD Quintile 2	CPIV STD Quintile 3	CPIV STD Quintile 4	High CPIV STD Quintile
Low CPIV Quintile	0.878	0.656	0.324	-0.036	-0.328
CPIV Quintile 2	0.724	0.577	0.635	0.476	0.588
CPIV Quintile 3	0.739	0.602	0.763	0.715	0.776
CPIV Quintile 4	0.694	0.683	0.854	0.766	0.927
High CPIV Quintile	0.595	0.519	0.691	0.672	1.153
High-Low	-0.283	-0.137	0.367	0.708	1.481
t-stat	(4.84)	(2.43)	(6.29)	(11.56)	(20.69)

Table 3: Double Sorts on CPIV and CPIV STD

Table 3 presents one-day, five-day and twenty-day returns after dividing the sample into quintiles based on CPIV and CPIV STD. In Panel A firms are sorted each day based on CPIV and further within these quintiles based on CPIV STD. In Panel B firms are sorted independently into quintiles based on CPIV and CPIV STD. In Panel A returns are also presented after sorting firms into quintiles based only on CPIV STD. High-low differences across CPIV STD quintiles and associated t-statistics are also presented. CPIV is the open interest weighted call implied volatility less open interest weighted put implied volatility. CPIV STD is the standard deviation of CPIV over the past 20 days. CPIV and CPIV STD are calculated using all options with 90 or fewer days to expiration.

Panel A: Dependent Sorts

One-Day Return	All	Low CPIV Quintile	CPIV Quintile 2	CPIV Quintile 3	CPIV Quintile 4	High CPIV Quintile
Low CPIV STD Quintile	0.040	-0.001	0.022	0.043	0.059	0.073
CPIV STD Quintile 2	0.033	-0.003	0.014	0.022	0.046	0.079
CPIV STD Quintile 3	0.033	-0.017	0.030	0.028	0.041	0.078
CPIV STD Quintile 4	0.036	-0.033	0.005	0.044	0.053	0.105
High CPIV STD Quintile	0.030	-0.091	0.026	0.050	0.066	0.124
High-Low	-0.011	-0.090	0.004	0.006	0.007	0.051
t-stat	(1.62)	(5.00)	(0.31)	(0.55)	(0.60)	(3.23)

Five-Day Return	All	Low CPIV Quintile	CPIV Quintile 2	CPIV Quintile 3	CPIV Quintile 4	High CPIV Quintile
Low CPIV STD Quintile	0.186	0.077	0.116	0.232	0.238	0.209
CPIV STD Quintile 2	0.148	0.059	0.134	0.142	0.177	0.198
CPIV STD Quintile 3	0.153	0.056	0.177	0.161	0.192	0.223
CPIV STD Quintile 4	0.165	-0.051	0.112	0.183	0.225	0.262
High CPIV STD Quintile	0.133	-0.202	0.144	0.183	0.255	0.419
High-Low	-0.053	-0.279	0.027	-0.049	0.017	0.210
t-stat	(3.66)	(6.98)	(1.00)	(1.95)	(0.64)	(5.86)

Twenty-Day Return	All	Low CPIV Quintile	CPIV Quintile 2	CPIV Quintile 3	CPIV Quintile 4	High CPIV Quintile
Low CPIV STD Quintile	0.721	0.508	0.603	0.801	0.848	0.677
CPIV STD Quintile 2	0.609	0.354	0.583	0.662	0.670	0.749
CPIV STD Quintile 3	0.654	0.118	0.689	0.683	0.754	0.600
CPIV STD Quintile 4	0.485	0.103	0.536	0.713	0.761	0.832
High CPIV STD Quintile	0.532	-0.447	0.639	0.702	0.815	1.039
High-Low	-0.188	-0.955	0.035	-0.099	-0.034	0.362
t-stat	(6.73)	(12.52)	(0.65)	(1.99)	(0.65)	(5.30)

Panel B: Independent Sorts

One-Day Return	Low CPIV Quintile	CPIV Quintile 2	CPIV Quintile 3	CPIV Quintile 4	High CPIV Quintile
Low CPIV STD Quintile	0.029	0.030	0.038	0.044	0.074
CPIV STD Quintile 2	0.034	0.022	0.018	0.037	0.063
CPIV STD Quintile 3	-0.009	0.007	0.035	0.057	0.074
CPIV STD Quintile 4	-0.029	0.010	0.051	0.060	0.095
High CPIV STD Quintile	-0.087	0.024	0.057	0.081	0.126
High-Low	-0.116	-0.006	0.019	0.037	0.052
t-stat	(7.09)	(0.44)	(1.35)	(2.68)	(3.51)

Five-Day Return	Low CPIV Quintile	CPIV Quintile 2	CPIV Quintile 3	CPIV Quintile 4	High CPIV Quintile
Low CPIV STD Quintile	0.189	0.160	0.201	0.182	0.211
CPIV STD Quintile 2	0.156	0.146	0.114	0.183	0.142
CPIV STD Quintile 3	0.042	0.112	0.181	0.239	0.191
CPIV STD Quintile 4	0.021	0.126	0.216	0.238	0.255
High CPIV STD Quintile	-0.208	0.129	0.206	0.280	0.408
High-Low	-0.397	-0.031	0.004	0.099	0.197
t-stat	(11.18)	(0.97)	(0.14)	(3.27)	(6.06)

Twenty-Day Return	Low CPIV Quintile	CPIV Quintile 2	CPIV Quintile 3	CPIV Quintile 4	High CPIV Quintile
Low CPIV STD Quintile	0.878	0.724	0.739	0.694	0.595
CPIV STD Quintile 2	0.656	0.577	0.602	0.683	0.519
CPIV STD Quintile 3	0.324	0.635	0.763	0.854	0.691
CPIV STD Quintile 4	-0.036	0.476	0.714	0.766	0.672
High CPIV STD Quintile	-0.328	0.588	0.776	0.926	1.153
High-Low	-1.206	-0.135	0.037	0.232	0.558
t-stat	(17.89)	(2.13)	(0.60)	(3.84)	(8.83)

Table 4: Fama-MacBeth Regressions

This table presents coefficients and significance levels for monthly Fama-MacBeth regressions. The dependent variable is monthly return. CPIV is the open interest weighted call implied volatility less open interest weighted put implied volatility. CPIV STD is the standard deviation of CPIV over the past 20 days. High STD takes a value of CPIV if the first in the top monthly quintile for CPIV STD. IV is open interest weighted implied volatility. Reversal is return in the calendar month prior to CPIV measurement. Momentum [-13,-2] is return in calendar months -13 through -2 relative to the date of CPIV measurement. Turnover[-1] is turnover from the month prior to CPIV measurement. Illiquidity[-22,-1] is the illiquidity measure of Amihud (2002) over the 21 calendar days prior to CPIV measurement. All measures using implied volatility are calculated using all options with 90 or fewer days to expiration. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

	Model (1)	Model (2)	Model (3)
Intercept	0.708 *	0.715 **	0.757 **
CPIV	0.030 ***	0.031 ***	0.020 **
CPIV STD		-0.747	-0.712
High STD			0.229 *
IV	-0.351	-0.343	-0.651
ME	-0.129	0.802	1.058
Reverse [-13,-2]	0.192	0.289	0.386
Momentum[-13,-2]	-0.346	-0.452	-0.510
Turnover[-1]	-0.075	-0.075	-0.071
Illiquidity [-22,-1]	-0.151	-0.021	0.089

Table 5: Five-Factor Regressions by CPIV

Table 5 presents coefficients and significance levels from five-factor regressions (Fama and French 2015) where the independent variable is the mean return of all firms in the given CPIV quintile. Results are presented for daily and monthly returns. CPIV is the open interest weighted call implied volatility less open interest weighted put implied volatility. CPIV is calculated using all options with 90 or fewer days to expiration.

Panel A: Daily Returns	Low CPIV Quintile	CPIV Quintile 2	CPIV Quintile 3	CPIV Quintile 4	High CPIV Quintile
Intercept	-0.060 ***	-0.015 ***	0.004	0.020 ***	0.060 ***
MKT	1.151 ***	1.122 ***	1.079 ***	1.089 ***	1.179 ***
SMB	0.692 ***	0.423 ***	0.345 ***	0.371 ***	0.585 ***
HML	0.271 ***	0.062 ***	-0.049 ***	-0.136 ***	-0.073 ***
RMW	-0.312 ***	-0.050 ***	-0.054 ***	-0.143 ***	-0.363 ***
CMA	-0.444 ***	-0.197 ***	-0.078 ***	-0.035 *	-0.344 ***

Panel B: Monthly Returns	Low CPIV Quintile	CPIV Quintile 2	CPIV Quintile 3	CPIV Quintile 4	High CPIV Quintile
Intercept	-0.746 ***	-0.069	0.091	0.152	0.257
MKT	1.236 ***	1.131 ***	1.112 ***	1.089 ***	1.173 ***
SMB	0.863 ***	0.495 ***	0.356 ***	0.442 ***	0.739 ***
HML	0.248 ***	0.072	-0.139 ***	-0.109 **	-0.078
RMW	0.020	-0.030	-0.153 **	-0.138 *	-0.400 ***
CMA	-0.525 ***	-0.250 **	-0.127	-0.015	-0.155

Table 6: Five-factor regressions by CPIV STD and CPIV

Table 6 presents coefficients and significance levels from five-factor regressions (Fama and French 2015) where the independent variable is the mean return of all firms in the given CPIV STD/CPIV group. In Panel A firms are sorted each period based on CPIV STD and further within these quintiles based on CPIV. In Panel B firms are sorted independently into quintiles based on CPIV STD and CPIV. Results are presented for daily and monthly returns. CPIV is the open interest weighted call implied volatility less open interest weighted put implied volatility. CPIV is calculated using all options with 90 or fewer days to expiration. CPIV is the open interest weighted call implied volatility less open interest weighted put implied volatility. CPIV STD is the standard deviation of CPIV over the past 20 days. CPIV and CPIV STD are calculated using all options with 90 or fewer days to expiration.

Panel A: Dependent Sorts and Daily Returns

	Low CPIV STD Quintile		CPIV STD Quintile 2		CPIV STD Quintile 3		CPIV STD Quintile 4		High CPIV STD Quintile	
Low CPIV Quintile	-0.022	***	-0.016	*	-0.045	***	-0.066	***	-0.141	***
CPIV Quintile 2	-0.013	**	-0.012		-0.025	***	-0.017		-0.020	
CPIV Quintile 3	0.012	**	-0.013	*	0.009		0.005		0.012	
CPIV Quintile 4	0.020	***	0.013	*	0.005		0.023	**	0.035	***
High CPIV Quintile	0.049	***	0.027	***	0.053	***	0.065	***	0.105	***

Panel B: Dependent Sorts and Monthly Returns

	Low CPIV STD Quintile		CPIV STD Quintile 2		CPIV STD Quintile 3		CPIV STD Quintile 4		High CPIV STD Quintile	
Low CPIV Quintile	-0.117		0.035		-0.470	*	-0.907	***	-1.849	***
CPIV Quintile 2	0.272	**	-0.212		0.070		-0.334		-0.207	
CPIV Quintile 3	0.055		-0.169		-0.139		0.086		0.202	
CPIV Quintile 4	0.187		0.151		0.327	*	0.081		0.397	
High CPIV Quintile	0.320	**	0.233		0.006		-0.028		0.418	

Panel C: Independent Sorts and Daily Returns

	Low CPIV STD Quintile	CPIV STD Quintile 2	CPIV STD Quintile 3	CPIV STD Quintile 4	High CPIV STD Quintile
Low CPIV Quintile	-0.031 **	-0.013	-0.045 ***	-0.058 ***	-0.105 ***
CPIV Quintile 2	-0.012 **	-0.016 **	-0.025 ***	-0.021 **	-0.007
CPIV Quintile 3	0.007	-0.013 *	0.004	0.013	0.015
CPIV Quintile 4	0.025 ***	0.009	0.017 **	0.021 **	0.044 ***
High CPIV Quintile	0.054 ***	0.035 ***	0.049 ***	0.065 ***	0.088 ***

Panel D: Independent Sorts and Monthly Returns

	Low CPIV STD Quintile	CPIV STD Quintile 2	CPIV STD Quintile 3	CPIV STD Quintile 4	High CPIV STD Quintile
Low CPIV Quintile	0.112	-0.027	-0.466 *	-0.829 ***	-1.440 ***
CPIV Quintile 2	-0.090	-0.139	0.068	-0.250	0.031
CPIV Quintile 3	0.170	-0.123	-0.134	0.169	0.600 *
CPIV Quintile 4	0.181	-0.046	0.345 *	-0.024	0.433
High CPIV Quintile	0.364 *	0.344 *	-0.043	0.061	0.336