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The Effects of Option Trading Behavior on Option Prices

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Abstract: This paper investigates the relationship between option trading behavior and option pricing patterns. We argue that greater active trading in the options market due to investor overconfidence leads to higher volatility and larger discrepancies in option pricing, which may be captured by implied volatility spread and implied volatility skewness. Using two different measures of excess option trading, we find that trading activities are correlated in different ways with volatility, volatility spread, and volatility skewness. We also find that these relationships exist both over time and cross-sectionally. We suggest that options investors tend to chase "hot" stocks, as we find evidence of a positive relationship between option trading activities and past underlying equity returns. Heavier trading in the options market also tends to make out-of-the-money call options more (less) expensive than the at-the-money counterparts over time (cross-sectionally). Because trading activities do not predict future equity returns, investor overconfidence, and not informed trading, seems to be a more plausible explanation for our findings.

Keywords: overconfidence; options market; option turnover; volatility spread; volatility smirk; behavioral finance

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1. Introduction

Trading behavior in the options market has drawn increasing attention from financial economists as the importance of the options market has increased, especially in recent years. While, theoretically, options can be replicated in a complete market, and some deem them redundant securities (Black and Scholes 1973), markets for these financial instruments have only grown larger. For example, CBOE reported a total trading volume of 3.4 billion as the number of contracts across all options products in North America in 2022, compared to 1.05 billion in 2015 and 254 million in 1999. Many financial scholars have focused on the study of the options market. Researchers have been striving to interpret the information content embedded in trading behavior. However, interpreting the information correctly is difficult if we fail to identify the actual motives for trading.

Scholars have proposed two main reasons why investors trade. One is differences of opinion, while the other is superior information. Both arguments suggest that investors trade because they hold beliefs that differ from those of general market participants, the latter of which are reflected in the current market prices. The two hypotheses are distinct in that the information-driven hypothesis assumes that investors who trade possess private information, whereas the differences-in-opinion hypothesis suggests that investors interpret the same information differently. While we observe the same increase in trading activities, the two hypotheses generate distinct inferences regarding how asset prices react to this information. Therefore, an understanding of the reasons for trading is crucial.

Studies identifying the reasons for trading options have shown mixed results. Starting from Black (1975), who argues that the leverage effects in options can attract informed traders, Amin and Lee (1997), Easley et al. (1998), Cao et al. (2005), and Pan and Poteshman

(2006) have found evidence supporting the information-driven hypothesis. On the other hand, Stephen and Whaley (1990), Vijh (1990), Chan et al. (1993, 2002), Muravyev et al. (2013), and Choy and Wei (2012) present evidence against informed trading.

In attempts to find reasons for excess trading activities in the stock market, researchers have found behavioral factors to be a logical fit. Grinblatt and Keloharju (2009) report that overconfidence and sensation-seeking lead to more frequent stock trading activities. More recently, Ülkü et al. (2023) have presented evidence supporting the idea that retail investors generally exhibit contrarian traits. Using trading data obtained from several countries during the COVID-19 pandemic, they also show that the net-trading direction between retail traders and institutional trades may diverge for an extended time period. While it has been shown in the literature that the options market plays an important informational role (e.g., Chakravarty et al. 2004), one may wonder what effects behavioral factors may have in this market. According to Scheinkman and Xiong (2003), investor overconfidence may intensify differences of opinion in the form of over-optimism for overconfident agents, and consequently create a price bubble. Also, bubbles are associated with large trading volumes and high price volatility. Empirically, Choy (2015) shows that retail investors speculate and are willing to pay a premium for future expected volatility, which provides evidence supporting a behavioral theory in the options market. A similar phenomenon can also be established during a negative bubble. Baig et al. (2022) studied the increased role played by retail investors during stressful times, including the 2008–2009 financial crisis and the COVID-19 pandemic. They document a negative impact of retail trading on the stability of stock prices that was particularly strong during the 2008–2009 financial crisis and the pandemic. The findings of Baig et al. (2022) and Ülkü et al. (2023) suggest that empirically examining whether there is a linkage between trading activities and measures of price bubbles and between trading and volatility is meaningful for understanding option trading and its information content.

This paper addresses two main research questions. First, we investigate the relationship between option trading activities and option prices and volatility over time. That is, we examine whether higher or lower volatility or discrepancy levels in option prices are associated with a higher option turnover rate. According to Scheinkman and Xiong (2003), volatility and price bubbles would intensify when there was an increase in trading activities. It is therefore natural to examine how volatility and option pricing patterns develop over time due to excessive trading.

Second, we investigate whether investor sentiment affects option pricing cross-sectionally. Options with higher turnover rates may behave differently than would those with lower turnover rates, should behavioral factors play a significant role in option prices. As Grinblatt and Keloharju (2009) point out, behavioral factors such as overconfidence and sensation-seeking tend to drive up trading activities. Regardless of the market they choose to trade in, overconfident agents may try to take advantage of their information (or beliefs) and consequently trade more frequently. Therefore, we use option turnover rate as a proxy for investor overconfidence and test the hypotheses of there being relationships between overconfidence and option volatility and option pricing. Cremers and Weinbaum (2010) use the difference in implied volatility between pairs of call and put options (volatility spread) to measure the relative expensiveness of call options over put options. Volatility spread may serve as a good indicator in examining whether call options become more expensive relative to the corresponding put options when the market presents evidence of overconfidence. As stated above, we expect to observe a positive relationship between the overconfidence measure and volatility spread.

The rest of the paper is organized as follows. The next section includes a review of the related literature. Section 3 discusses the research questions and empirical methodology. Section 4 provides the empirical results. The last section includes a discussion of the paper's findings and their implications.

2. Literature Review

2.1. Overconfidence and Momentum

Both momentum (Jegadeesh and Titman 1993) and reversals (DeBondt and Thaler 1985) are well documented in the stock market literature. While a momentum strategy that buys winning stocks and short-sells losing stocks generates superior average returns in the short run, it results in negative average returns in the long run (reversals). A simple but popular explanation that fits both phenomena is behavioral. The behavioral theories that try to address the issue include Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999), and George and Hwang (2004). Among those theories, Daniel et al. (1998) attribute the phenomena to the behavior of overconfident agents. In their framework, investors bear self-attribution bias; that is, they tend to attribute their success in investment to their trading skills and knowledge and blame their failure on bad luck or unpredictable noises. This theory is empirically supported by Lee and Swaminathan (2000), Statman et al. (2006), and Cremers and Pareek (2014), to name a few. While evidence from stock markets generally supports the self-attribution bias, even for institutional investors (Cremers and Pareek 2014), the existence and the potential influence of such a bias are largely not discussed in the literature.

2.2. Price Patterns in the Options Market

Options market pricing has intrigued financial economists in various ways for decades. One of the heavily discussed topics is the existence of arbitrage opportunities. Initially, options were deemed to be redundant securities (Black and Scholes 1973; Cox et al. 1979), and investors should have no reason to trade such financial instruments. However, scholars have empirically identified deviations from basic option pricing rules such as put–call parity (e.g., Ofek et al. 2004) which provide incentives for investors to trade in the options market.

The argument about the existence of arbitrage opportunities goes on, as other researchers have shown evidence against those findings (e.g., Battalio and Schultz 2006). Even if deviations exist from no-arbitrage relations, most will agree that the arbitrage opportunities dissipate fairly quickly. They can hardly account for the extensive trading activities in the options market. Cremers and Weinbaum (2010), on the other hand, argue that the relative expensiveness of put and call options, as paired with strike price and that of the underlying security, may predict future stock performance. Their findings provide further reasons for trading, suggesting that predictability comes from the mispricing of options. Coinciding with Cremers and Weinbaum (2010), Xing et al. (2010) found that the shape of a volatility smirk predicts future stock returns. Some papers suggest that informed traders may lead the trading in the options market due to leverage (Black 1975) and reveal their information within option prices. While others argue that differences of opinion are the main reason for trading (Choy and Wei 2012), the causes of differences of opinion remain largely uninvestigated.

3. Research Questions and Empirical Methodology

This study aims to test the relationship between trading activities and option prices empirically. Grinblatt and Keloharju (2009) show the connections between more frequent trading activities, overconfidence, and sensation seeking. As suggested in Scheinkman and Xiong (2003), investor overconfidence intensifies differences of opinion and therefore causes heavier trading. Higher volatilities, as well as price bubbles, accompany heavier trading. When investors trade, not based on information, but on behavioral factors, we expect trading activities to be higher than usual. Also, it is more likely to observe a price bubble in the corresponding market. Building upon the abovementioned expectations, this paper empirically tests the relationship between excessive trading activities and option price patterns.

3.1. Empirical Methodology

Our first objective is to capture excessive trading activities. We propose two measures for this purpose. Following Statman et al. (2006), two control variables are used to account for normal trading motives. The first control variable is market volatility, misg, based on the research by Karpoff (1987) on the contemporaneous volume–volatility relationship. The second control variable is dispersion, disp, which is associated with the idiosyncratic risk of the underlying stock and therefore accounts for trading activities related to portfolio rebalancing. In addition, we include proportional effective spread, sprd, to control for liquidity. Specifically, the proportional effective spread (a measure of illiquidity) for underlying equity j on day D is calculated as follows:

$$sprd_{D,j} = \frac{1}{Vol_{D,j}} \sum_{k=1}^{n} Vol_{D,j,k} \times 100 \times \frac{2 \times \left(Offer_{D,j,k} - Bid_{D,j,k}\right)}{\left(Offer_{D,j,k} + Bid_{D,j,k}\right)} \tag{1}$$

where $Vol_{D,j} = \sum_{k=1}^{n} Vol_{D,j,k}$, and k stands for different strike prices. The primary measure of trading volume used in this study is option trading turnover, TO_O, which is defined as option trading volume multiplied by 100, scaled by open interest. The model is as follows:

$$TO\_O_t = a + b_1 \times misg_t + b_2 \times disp_t + b_3 \times sprd_t + \varepsilon_t \tag{2}$$

We extract the residuals from the above regression and use them as our first measure of overconfidence over time.

In addition to the above measure, we apply the stochastic frontier analysis (SFA) technique to isolate the potential trading behavior due to overconfidence from the behavior based on random information flows. The rationale behind using SFA in this study is that we treat overconfidence as a systematic bias for investors, which constantly drives up trading volume. Since the standard ordinary least square method does not distinguish between systematic bias in trading and purely stochastic component in trading activities, SFA's capability to capture the systematic bias via skewness in residuals would help extract trading activities due to overconfidence. We use the following regression model:

$$TO\_O_t = a + b_1 \times misg_t + b_2 \times disp_t + b_3 \times sprd_t + v_t + u_t \tag{3}$$

where u_t is a one-sided error half normally distributed $N(0^+, \sigma_u^2)$.

We adopt two inefficiency measures in this study. Both are based on technical efficiency measures. That is, $OC_i = 1 - TE_i$, where $i = 1, 2$. TE_1 is the technical efficiency measure used by Battese and Coelli (1988), and TE_2 is the technical efficiency measure used by Jondrow et al. (1982).

Once the overconfidence measure is obtained, we test the relationships between overconfidence and price volatility and price bubble measures. We use the following two measures for volatility: VIX and realized volatility over the past 30 days. The change in volatility is also included as a dependent variable. We use volatility spread and volatility smirk (skewness) for price bubble measures. Volatility spread, proposed by Cremers and Weinbaum (2010), measures the relative expensiveness of calls and puts with the same strike price. Cremers and Weinbaum find that the stocks with relatively expensive calls outperform stocks with relatively expensive puts. They also document that this finding is likely due to the information risk that the underlying stocks face. If investors in the options market are overly optimistic about the performance of the underlying stock, we should observe more expensive call options relative to put options with the same strike. In such a case, the subsequent superior performance they have documented may be explained as the confidence building up in the options market and then spilling over to the underlying stock market.

A similar argument can be applied to volatility smirk, which measures the relative expensiveness of in-the-money and out-of-the-money calls (puts). As in the case of calls, the general explanation is that in-the-money call options offer leverage and, therefore, a more promising strategy for investors who wish to take long positions. As investors become overly optimistic, we should observe more expensive in-the-money call options and less expensive out-of-the-money put options (fewer hedging activities using puts). Consequently, the volatility smirk for calls (puts) will become steeper (flatter).

3.2. Hypotheses

Based on our discussion above, we test the following hypotheses in this paper:

H1. *Higher investor overconfidence leads to both higher expected volatility and higher subsequently realized volatility.*

H2. *Higher investor overconfidence makes call options more expensive than the corresponding put options with the same strike price.*

H3. *Higher investor overconfidence results in more expensive in-the-money/at-the-money call options relative to the out-of-the-money options and less expensive out-of-the-money put options relative to the in-the-money/at-the-money options.*

Time series regressions were conducted to test the above hypotheses. In addition to examining the relationships between investor overconfidence and asset prices over time, we also examined the impacts across firms. Both Cremers and Weinbaum (2010) and Xing et al. (2010) find that the differences in implied volatilities predict future equity returns. While Cremers and Weinbaum indicate that mispricing is the main reason for this finding, Xing et al. argue that informed traders may be the driving force.

In both studies, the authors first sorted the sample firms into portfolios according to volatility spread/skew/smirk, and then showed differences in future performance across portfolios. If investor overconfidence played a specific role in their findings, one should expect that overconfidence measures would be associated with volatility spread/skew/smirk cross-sectionally. For instance, Cremers and Weinbaum found that stocks with more expensive calls or with calls becoming more expensive than in the previous periods earned abnormal positive returns, while the ones with more expensive puts or with puts becoming more expensive than in the previous period earned abnormal negative returns. If firms with more frequent trading activities generally have more expensive calls, the subsequent abnormal returns documented by Cremers and Weinbaum may be the price bubble suggested by Scheinkman and Xiong (2003). A similar argument applies to the predictability of future stock returns according to volatility skew/smirk, as argued by Xing et al. Therefore, we conducted a second series of tests to examine the relationships between trading activities and volatility spread/skew/smirk across firms.

3.3. Data

The option data was retrieved from OptionMetrics (New York, NY, USA) via WRDS. End-of-day bid and ask quotes, open interests, trading volume, and implied volatility were obtained from the database for the period ranging from January 1996 to December 2011. The sample included 2779 unique firms listed on NYSE/AMEX, and with options traded. In addition to the option turnover rate, the O/S ratio was also used as a measure of trading activities. Since different practices in reporting trading volume in dealers' markets may cause inconsistency in the O/S ratio, the sample in this study consisted only of firms listed on NYSE/AMEX with options. VIX, a forward volatility index proposed by CBOE, was used as a measure of volatility for the entire market. End-of-day stock prices and trading volume were extracted from the Center for Research in Security Prices (CRSP).

Table 1 contains descriptive statistics for all the variables used in the empirical analyses. Panel A shows the characteristics of the primary dependent variables used in the empirical studies. Note that the percentage change in 30-day volatility has a mean and median close to zero. Volatility spread has a negative mean and median, as reported in Cremers and Weinbaum (2010), while volatility skew has a positive mean and median, consistent with Xing et al. (2010).

Table 1. Sample characteristics.

Panel A: Volatility Measures and Price Discrepancy Measures			
Measure	**Mean**	**Median**	**Std. Dev.**
% Change in VIX	0.0164	−0.0145	0.1800
% Change in 30-day Volatility	0.0002	0.0001	0.0130
30-day Realized Volatility	0.4617	0.4193	0.1914
Volatility Spread	−0.0091	−0.0079	0.0076
Volatility Skew	0.0458	0.0387	0.0237
Panel B: Overconfidence Measures			
Measure	**Mean**	**Median**	**Std. Dev.**
Option Turnover	3.8552	3.7904	0.9073
OLS Residual	0.0000	−0.1522	0.8498
OC1	7.3858	5.7913	5.3460
OC2	7.6567	5.9459	5.6454

This table shows summary statistics for variables used in this study. Panel A summarizes the mean, median, and standard deviation of the primary dependent variables used in the empirical analysis. The numbers shown for all variables, except for the percentage changes of volatility measures, are the daily averages over the sample period. Volatility change is the percentage changes in the daily average volatility of the corresponding month from that of the previous month. Volatility spread is the weighted average difference in implied volatility of paired call and put options with the same strike price and the same underlying equity, as specified in Cremers and Weinbaum (2010). Volatility skew is the difference between the implied volatility of out-of-the-money (OTM) put options and the implied volatility of at-the-money (ATM) call options. Panel B summarizes the mean, median, and standard deviation for the explanatory variables, which are used as a proxy of investor overconfidence. OC1 and OC2 are (1) residuals from ordinary least square regressions; and (2) overconfidence measures from stochastic frontier analysis (SFA), respectively.

Panel B summarizes the mean, median, and standard deviation for the explanatory variables, which are used as a proxy of investor overconfidence. OC1 and OC2 are the inefficiency measures derived from stochastic frontier analysis (SFA) and are very similar qualitatively and quantitatively. We expect they would yield similar results in the main empirical analyses.

4. Results

As discussed in the previous section, the main question addressed in this study is whether investor overconfidence plays a role in option pricing. To investigate this issue, we conducted two series of tests. The first set of tests ran regressions of trading activities, which is used as a proxy for investor overconfidence, on volatility measures and relative expensiveness across options. Before running this set of tests, we checked that the variables were stationary, in order to avoid spurious regressions. Specifically, we used augmented Dickey–Fuller and Phillip–Perron tests to check for the stationarity of all dependent and independent variables used in our regression analysis. The results of the tests on all independent variables (i.e., OLS residuals, OC1, and OC2) reject the null hypothesis of a unit root at the 1% level. The results of the tests on all dependent variables reject the null hypothesis of unit root at the 1% level, except for volatility skew (IV_SKEW) and volatility smirk (IV_SMIRK), for which the results reject the null hypothesis at the 5% level.

The second set of tests involved sorting sample firms into portfolios based on trading activities and examining the differences in volatility spread/skew/smirk across portfolios. This section provides the results of these two sets of tests.

4.1. Time-Series Regressions

To construct the measure of option trading activities, we aggregated daily trading volumes and open interests across all options for the entire sample of firms, and then divided the aggregated trading volume by the end-of-the-day aggregated open interest. We defined this ratio as the option turnover rate.

For changes in VIX, we obtained the daily VIX from WRDS and then took the average of the daily VIX over a calendar month. The changes in VIX are the percentage changes in daily average VIX in the current month from that of the previous month. Daily realized volatilities for sample firms were obtained from OptionMetrics. For each day of a given month, volatilities realized during the past 30 calendar days were extracted and averaged over the month. The changes in realized volatility are the percentage changes of average realized 30-day volatility in a given month as compared to those of the previous month.

The volatility spread was calculated daily for each sample firm and averaged over a month. Following Cremers and Weinbaum (2010), we paired call and put options with the same underlying equity, strike, and maturity, and then calculated volatility spread as the difference between the implied volatilities of the call and put options. Daily volatility spread was defined for each trading day as the weighted average spread for each pair of call and put options with the same strike price and maturity. Following Xing et al. (2010), implied volatility skew was calculated as the difference between the implied volatilities of OTM puts and ATM calls.

There are several ways to determine the moneyness of options. In this study, following Xing et al. (2010), an option is defined as OTM when the absolute delta of the option is at least 0.125 but less than 0.375. It is defined as ATM when the absolute delta is at least 0.375 but less than 0.625, and finally, it is defined as ITM when the absolute delta is at least 0.625 but less than 0.875. A simpler way to define moneyness is to use the ratio of the strike price to the stock price (K/S). Ni (2007) uses the total volatility-adjusted strike-to-stock-price ratio as another moneyness measure. However, these alternative methods yield quantitatively similar results.

Daily volatility skew was averaged across sample firms in a day, weighted by the end-of-the-day open interests. We computed monthly volatility skew by averaging the daily volatility skew over a month.

Table 2 presents the results of the first empirical test for all options (calls and puts). As mentioned in the previous section, the explanatory variables are derived from the first stage regression. The residuals are extracted from the first stage regression using the ordinary least square method, controlling for market volatility, idiosyncratic risk, and proportional effective spread. OC1 and OC2 are inefficiency measures derived from stochastic frontier analysis, assuming half normal distribution in inefficiency. Specifically, they are one minus the technical efficiency measures, as suggested by Battese and Coelli (1988) and Jondrow et al. (1982), respectively.

It is apparent that OLS residual and OC1/OC2 paint different pictures in this table. Focusing first on the results of the second-stage regression using OLS residuals as the explanatory variable, we find that OLS residuals are positively related to the percentage changes in expected and realized volatility measures from the previous month, with the F-statistics of the regressions being 2.95 and 5.18, respectively. These results serve as a piece of evidence supporting the theory in Scheinkman and Xiong (2003) that investor overconfidence intensifies differences of opinions and consequently causes higher volatility. On the other hand, OLS residuals and volatility spread are negatively correlated, with a regression F-statistic of 9.89. This suggests that an increase in the frequency of trading activities tends to make put options more expensive than call options.

OLS residuals and volatility skew are negatively correlated (the F-statistic is 3.23). This result is intriguing, as it indicates the presence of fewer hedging activities using OTM put options. Therefore, we further investigated the difference in implied volatilities across the moneyness of options. In the options market, implied volatility skew is negatively sloped across strike prices (higher implied volatility for ITM call options and OTM put options, relative to OTM call options and ITM put options). As shown in Figure 1, the pattern is clear throughout the sample period, while it tends to be more severe during a financial crisis. In both crises during the sample period, i.e., the post-dot-com bubble era and the 2007–2009 financial crisis, there were large spikes. Also, there is a tendency towards steeper slopes over time.

Table 2. Regression analysis—volatility measures and price discrepancy measures against unexpected turnovers on *all* options.

	Explanatory Variables			
Dependent Variables	**OLS Residual**	**OC1**	**OC2**	**Adj. R^2**
Percentage Change in VIX	0.0280 **	−0.0050 **	−0.0047 **	0.0144
	(0.0115)	(0.0020)	(0.0019)	
Past 30 Days' Realized Volatility	0.0000	−0.0018	−0.0017	−0.0015
	(0.0205)	(0.0030)	(0.0028)	
Volatility % Change—Past 30 Days	0.0044 ***	−0.0072 ***	−0.0007 ***	0.0778
	(0.0010)	(0.0014)	(0.0001)	
Volatility Spread	−0.0018 *	0.0003 ***	0.0003 ***	0.0384
	(0.0011)	(0.0001)	(0.0001)	
Changes in Volatility Spread	−0.0007	0.0001	0.0001	0.0045
	(0.0006)	(0.0001)	(0.0001)	
Volatility Skew	−0.0049 **	0.0009 **	0.0008 **	0.0264
	(0.0024)	(0.0004)	(0.0004)	
Changes in Volatility Skew	0.0006	−0.0002	−0.0002	0.0034
	(0.0010)	(0.0001)	(0.0001)	
Call Volatility Smirk (ATM–OTM)	−0.0042 **	0.0007 ***	0.0007 ***	0.0396
	(0.0018)	(0.0002)	(0.0002)	
Call Volatility Smirk (ITM–OTM)	−0.0077 *	0.0013 **	0.0012 **	0.0223
	(0.0040)	(0.0006)	(0.0005)	
Put Volatility Smirk (ATM–OTM)	0.0048 *	−0.0009 **	−0.0008 **	0.0256
	(0.0025)	(0.0004)	(0.0004)	
Put Volatility Smirk (ITM–OTM)	0.0095 **	−0.0017 ***	−0.0016 ***	0.0475
	(0.0038)	(0.0006)	(0.0005)	

The regressions use monthly aggregated market observations. Explanatory variables are overconfidence measures, using option turnovers from *all* options, and controlling for market volatility, idiosyncratic risk of the underlying stock, and proportional effective spread. Specifically, the overconfidence measures, OC1 and OC2, are (1) residuals from ordinary least square regressions; and (2) overconfidence measures from stochastic frontier analysis (SFA), respectively. Dependent variables are volatility measures and price discrepancy measures. The volatility spread is from Cremers and Weinbaum (2010), while the volatility skew is from Xing et al. (2010). Numbers in parentheses are standard errors. The adjusted R^2 values are the averages of the corresponding values of the three regressions. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

In tests of the volatility skew/smirk slope, we found that OLS residuals were associated with flatter slopes, which means less expensive ITM calls and OTM puts. The findings are indicated by negative (positive) coefficients on volatility smirk for call (put) options, and the coefficients are statistically significant at the 10% level. The F-statistics for these regressions range from 2.90 to 6.67, which implies the validity of the models at the 10% and 5% levels.

A natural explanation for this finding may be that overconfident agents try to take their chances in the options market, generating a higher demand for OTM call options. In comparison, they are less worried about market crashes, creating less demand for put options. While the finding from the slopes of the volatility smirk is consistent with the one from the volatility skew, it still does not explain the lower volatility spread. One possibility is that the volatility spread is weighted by open interests, reflecting the relative expensiveness of ATM call and put options. That is, ATM call options become less expensive than ATM put options. This might be due to the standard trading strategy of a covered call, which sells short ATM call options instead of dumping underlying equity into the market to increase portfolio returns.

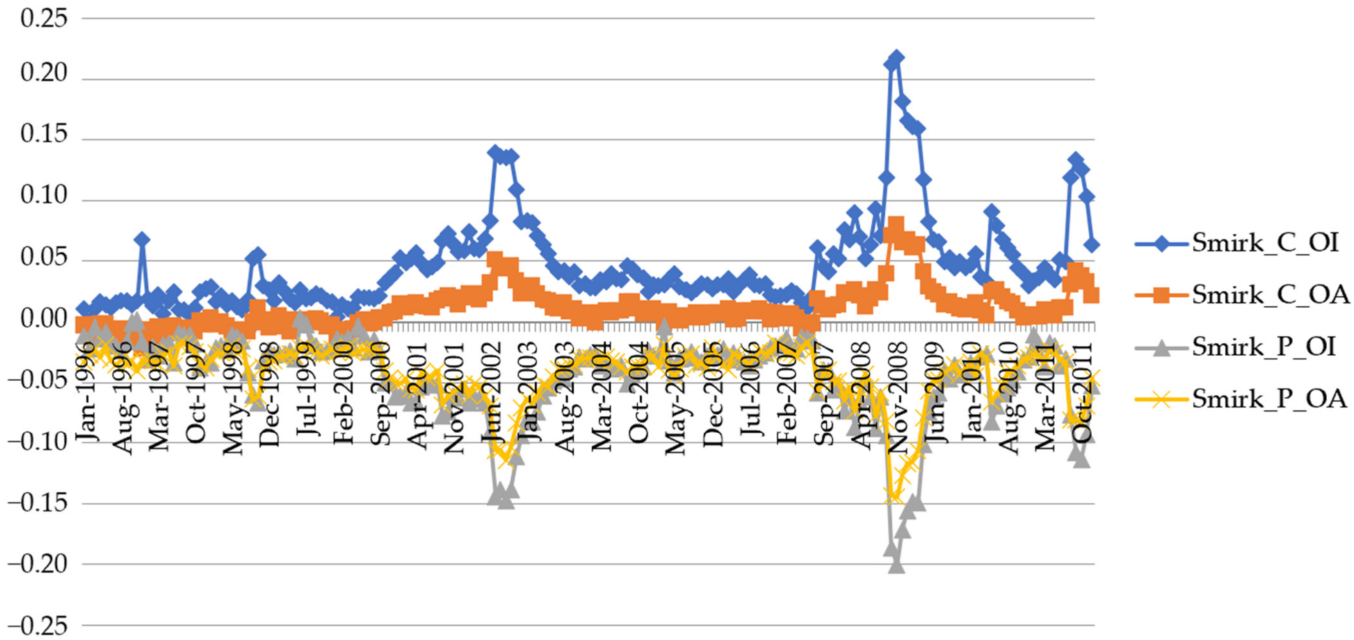

Figure 1. Volatility smirk over time. This figure exhibits an implied volatility smirk over time. Smirk_C_OA is the difference in implied volatility between ATM call options and OTM call options. Smirk_C_OI is the difference in implied volatility between ITM and OTM call options. Smirk_P_OA is the difference in implied volatility between ATM and OTM put options. Smirk_C_OA is the difference in implied volatility between ITM and OTM put options.

When we use inefficiency measures from SFA as a measure of investor overconfidence, we find a different picture. Both OC1 and OC2 are negatively correlated with changes in volatility measures from the previous month, while they are positively correlated with volatility spread (with F-statistics ranging from 7.96 to 18.12). In addition, there is a positive correlation between investor overconfidence measures and the steepness of volatility smirk across strike prices (with F-statistics ranging from 6.45 to 12.51). As the methodology section explains, OC1 and OC2 are technical inefficiency measures derived from SFA. Therefore, we see them as overly aggressive trading activities and as proxies for investor overconfidence. The results, in sum, do not agree with the argument.

First, we find negative and statistically significant coefficients for volatility measures. This suggests that OC1 and OC2 capture trading activities when option prices are relatively stable and expected to stay stable. The findings from volatilities are consistent with the ones from volatility skew/smirk. A general argument for the existence of volatility skew/smirk is that investors are worried about a market crash and, therefore, would like to protect their holdings by buying more OTM put options. Another popular explanation is that investors use ATM/ITM call options instead of their stock investments to enhance rates of return. Both explanations are supported in this line of tests, given that OC1 and OC2 are positively correlated with volatility skew (more expansive OTM puts than ATM calls) and with the slope of the volatility smirk. Again, volatility spread positively correlates with OC1 and OC2, which may seem to contradict the previous argument. As explained above, ATM call and put options may be driving this finding.

We conducted similar tests using call and put option turnover ratios, as described in Tables 3 and 4, respectively. The results are qualitatively similar across the three tables, as most coefficients appear in the same signs with their corresponding peers in all three tables, and no surprisingly larger or smaller coefficient is identified. The only noticeable difference is that put option turnover seems to have better explanatory power for volatility skew/smirk (and also with significantly higher F-statistics of 8.80 to 14.11 and higher adjusted R^2 of 0.0251 to 0.0453). This is consistent with the argument that investors in the options market favor using put options to avoid massive losses in a significant market crash. The findings are more pronounced when OC1 and OC2 are used as measures of excess trading, which may suggest that the inefficiency trading measures derived from SFA capture investors' fears of market crashes.

Table 3. Regression analysis—volatility measures and price discrepancy measures against unexpected turnovers on *call* options.

	Explanatory Variables			
Dependent Variables	**OLS Residual**	**OC1**	**OC2**	**Adj. R^2**
Percentage Change in VIX	0.0266 **	−0.0063 ***	−0.0060 ***	0.0168
	(0.0135)	(0.0023)	(0.0022)	
Past 30 Days' Realized Volatility	0.0161	−0.0014	−0.0013	−0.0027
	(0.0200)	(0.0037)	(0.0036)	
Volatility % Change—Past 30 Days	0.0036 ***	−0.0008 ***	−0.0008 ***	0.0690
	(0.0010)	(0.0002)	(0.0002)	
Volatility Spread	−0.0025 **	0.0004 ***	0.0003 ***	0.0520
	(0.0012)	(0.0001)	(0.0001)	
Volatility Skew	−0.0022	0.0006	0.0006	0.0066
	(0.0023)	(0.0005)	(0.0004)	
Call Volatility Smirk (ATM–OTM)	−0.0019	0.0005 *	0.0005 **	0.0124
	(0.0017)	(0.0003)	(0.0003)	
Call Volatility Smirk (ITM–OTM)	−0.0027	0.0009	0.0008	0.0033
	(0.0039)	(0.0007)	(0.0007)	
Put Volatility Smirk (ATM–OTM)	0.0021	−0.0006	−0.0006	0.0066
	(0.0024)	(0.0005)	(0.0005)	
Put Volatility Smirk (ITM–OTM)	0.0053	−0.0013 **	−0.0013 **	0.0195
	(0.0036)	(0.0007)	(0.0006)	

The regressions use monthly aggregated market observations. Explanatory variables are overconfidence measures, using option turnovers from call options, and controlling for market volatility, idiosyncratic risk of the underlying stock, and proportional effective spread. Specifically, the overconfidence measures, OC1 and OC2, are (1) residuals from ordinary least square regressions; and (2) overconfidence measures from stochastic frontier analysis (SFA), respectively. Dependent variables are volatility measures and price discrepancy measures. The volatility spread is from Cremers and Weinbaum (2010), while the volatility skew is from Xing et al. (2010). Numbers in parentheses are standard errors. The adjusted R^2 values are the averages of the corresponding values for the three regressions. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

To further explore the above findings, we divided all sample firms into two groups according to the percentage of institutional holdings of the firm. Since institutional investors are less likely to be subject to behavioral biases, if a pattern is more pronounced in the group with lower institutional ownership, the pattern is more likely due to behavioral biases, such as investor overconfidence.

To form the two portfolios, we set the cutoff point at the median percentage of institutional holdings of the entire sample. This sorting resulted in each group having an equal number of firms. By comparing Panel A and Panel B in Table 5, we find very similar results in most of the tests, except the one for volatility spread. All trading measures exhibit a lack of explanatory power as to volatility spread for the group with higher institutional ownership. In comparison, they appear to be highly correlated with volatility spread for the group with lower institutional ownership. Again, OLS residuals are negatively correlated with volatility spread in this table, while OC1 and OC2 are positively correlated with volatility spread. Given that volatility spread is dominated by the demand for ATM call options relative to put options, one may conclude that OLS residuals capture demands on put options while OC1 and OC2 capture demands on call options.

Table 4. Regression analysis—volatility measures and price discrepancy measures against unexpected turnovers on *put* options.

	Explanatory Variables			
Dependent Variables	**OLS Residual**	**OC1**	**OC2**	**Adj. R^2**
Percentage Change in VIX	0.0406 *** (0.0157)	−0.0056 *** (0.0021)	−0.0053 *** (0.0020)	0.0224
Past 30 Days' Realized Volatility	0.0289 (0.0212)	−0.0018 (0.0033)	−0.0017 (0.0031)	0.0013
Volatility % Change—Past 30 Days	0.0053 *** (0.0011)	−0.0008 *** (0.0001)	−0.0008 *** (0.0001)	0.0962
Volatility Spread	−0.0012 (0.0009)	0.0002 * (0.0001)	0.0002 * (0.0001)	0.0099
Volatility Skew	−0.0017 (0.0027)	0.0009 ** (0.0004)	0.0009 ** (0.0004)	0.0236
Call Volatility Smirk (ATM–OTM)	−0.0026 (0.0021)	0.0008 *** (0.0002)	0.0008 *** (0.0002)	0.0439
Call Volatility Smirk (ITM–OTM)	−0.0040 (0.0048)	0.0016 *** (0.0006)	0.0015 *** (0.0006)	0.0283
Put Volatility Smirk (ATM–OTM)	0.0013 (0.0030)	−0.0010 ** (0.0004)	−0.0009 ** (0.0004)	0.0251
Put Volatility Smirk (ITM–OTM)	0.0050 (0.0045)	−0.0018 *** (0.0006)	−0.0017 *** (0.0006)	0.0453

The regressions use monthly aggregated market observations. Explanatory variables are overconfidence measures, using option turnovers from put options, and controlling for market volatility, idiosyncratic risk of the underlying stock, and proportional effective spread. Specifically, the overconfidence measures, OC1 and OC2, are (1) residuals from ordinary least square regressions; and (2) overconfidence measures from stochastic frontier analysis (SFA), respectively. Dependent variables are volatility measures and price discrepancy measures. The volatility spread is from Cremers and Weinbaum (2010), while the volatility skew is from Xing et al. (2010). Numbers in parentheses are standard errors. The adjusted R^2 values are the averages of the corresponding values for the three regressions. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 5. Unexpected turnovers on all options against volatility measures and price discrepancy measures—sorted by institutional ownership.

Panel A: High Institutional Ownership				
	Explanatory Variables			
Dependent Variables	**OLS Residual**	**OC1**	**OC2**	**Adj. R^2**
Percentage Change in VIX	1.4638 (1.4622)	−0.3828 ** (0.1949)	−0.3653 ** (0.1848)	0.0033
Past 30 Days' Realized Volatility	−0.0008 (0.0200)	0.0006 (0.0030)	0.0006 (0.0028)	−0.0051
Volatility % Change—Past 30 Days	0.4590 *** (0.1090)	−0.0740 *** (0.0197)	−0.0704 *** (0.0186)	0.0983
Volatility Spread	0.0674 (0.0456)	−0.0022 (0.0060)	−0.0021 (0.0057)	−0.0020
Volatility Skew	−0.3179 (0.2778)	0.0719 * (0.0398)	0.0686 * (0.0378)	0.0108
Call Volatility Smirk (ATM–OTM)	−0.3389 * (0.1805)	0.0636 *** (0.0229)	0.0606 *** (0.0217)	0.0307
Call Volatility Smirk (ITM–OTM)	−0.0062 (0.0041)	0.0012 ** (0.0006)	0.0012 ** (0.0005)	0.0196
Put Volatility Smirk (ATM–OTM)	0.3506 (0.2586)	−0.0782 ** (0.0362)	−0.0746 ** (0.0344)	0.0179
Put Volatility Smirk (ITM–OTM)	0.0076 * (0.0040)	−0.0016 *** (0.0006)	−0.0016 *** (0.0005)	0.0386

Table 5. *Cont.*

Panel B: Low Institutional Ownership				
	Explanatory Variables			
Dependent Variables	**OLS Residual**	**OC1**	**OC2**	**Adj. R^2**
Percentage Change in VIX	1.5253	−0.4060 **	−0.3833 **	0.0086
	(1.4289)	(0.1781)	(0.1670)	
Past 30 Days' Realized Volatility	0.0317 *	−0.0036	−0.0034	0.0101
	(0.0190)	(0.0029)	(0.0027)	
Volatility % Change—Past 30 Days	0.4071 ***	−0.0647 ***	−0.0607 ***	0.0561
	(0.1063)	(0.0144)	(0.0136)	
Volatility Spread	−0.3161 **	0.0356 ***	0.0332 ***	0.0539
	(0.1479)	(0.0133)	(0.0124)	
Volatility Skew	−0.3141	0.0746 *	0.0703 *	0.0197
	(0.2449)	(0.0414)	(0.0388)	
Call Volatility Smirk (ATM–OTM)	−0.2928 *	0.0603 ***	0.0568 ***	0.0329
	(0.1736)	(0.0212)	(0.0199)	
Call Volatility Smirk (ITM–OTM)	−0.0045	0.0011 *	0.0011 *	0.0171
	(0.0040)	(0.0006)	(0.0005)	
Put Volatility Smirk (ATM–OTM)	0.2967	−0.0809 **	−0.0762 **	0.0244
	(0.2488)	(0.0403)	(0.0378)	
Put Volatility Smirk (ITM–OTM)	0.0063 *	−0.0014 **	−0.0013 **	0.0388
	(0.0036)	(0.0006)	(0.0005)	

We sorted the sample into two subsamples according to institutional ownership. Firms with a percentage of institutional ownership above (below) the sample median are considered high (low) institutional ownership. This table reports the regression results for these two subsamples using monthly aggregated market observations. Explanatory variables are overconfidence measures, using option turnovers from all options, and controlling for market volatility, idiosyncratic risk of the underlying stock, and proportional effective spread. Specifically, the overconfidence measures, OC1 and OC2, are (1) residuals from ordinary least square regressions; and (2) overconfidence measures from stochastic frontier analysis (SFA), respectively. Dependent variables are volatility measures and price discrepancy measures. The volatility spread is from Cremers and Weinbaum (2010), while the volatility skew is from Xing et al. (2010). Numbers in parentheses are standard errors. The adjusted R^2 values are the averages of the corresponding values for the three regressions. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

4.2. Cross-Sectional Analysis

As suggested in Cremers and Weinbaum (2010) and Xing et al. (2010), differences in implied volatility may predict future equity returns. While informed traders, as shown in both studies, may well be the driving force in the findings, we wanted to explore whether there might be an alternative explanation. Unlike some demand-based trading activity measures used in studies such as Pan and Poteshman (2006), option turnover ratios are publicly available information. It would be challenging to argue that informed traders are fully accountable for the predictability of volatility spread/skew/smirk if the volatility patterns are directly tied to observable trading activities. Therefore, we conducted a set of simple tests to examine if there was a cross-sectional connection between volatility patterns and trading activities.

First, we sorted the sample firms into deciles based on monthly average trading turnover and calculated the volatility patterns for each decile. All of the volatility patterns for each decile were weighted based on open interest. Table 6 depicts various trading measures, including all (calls and puts) option turnover, call option turnover, put option turnover, O/S ratio, and O/S ratio in USD value (DOS). Regardless of which trading measure is used, we observe a monotonic pattern on volatility spread across trading deciles, where more heavily traded portfolios have a more negative volatility spread. Also, the differences in volatility spread between the most and the least active portfolios are statistically significant across all measures.

Table 6. Cross-Sectional analyses—trading activities against price discrepancy measures.

Panel A: All Option Turnover												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	***Diff***	***t*-Stat**
VS	−0.0060	−0.0069	−0.0068	−0.0074	−0.0072	−0.0078	−0.0078	−0.0080	−0.0086	−0.0091	−0.0031	−6.08
IV_Skew	0.0460	0.0466	0.0448	0.0441	0.0433	0.0433	0.0430	0.0449	0.0454	0.0489	0.0029	0.93
Smirk_C_OA	0.0020	0.0044	0.0061	0.0071	0.0073	0.0083	0.0089	0.0085	0.0091	0.0092	0.0071	3.44
Smirk_C_OI	0.0311	0.0328	0.0324	0.0337	0.0332	0.0344	0.0352	0.0360	0.0371	0.0392	0.0082	2.47
Smirk_P_OA	−0.0327	−0.0355	−0.0345	−0.0343	−0.0340	−0.0341	−0.0341	−0.0349	−0.0358	−0.0365	−0.0038	−1.28
Smirk_P_OI	−0.0254	−0.0292	−0.0289	−0.0301	−0.0312	−0.0327	−0.0333	−0.0344	−0.0350	−0.0362	−0.0108	−2.96
Return	−0.0079	−0.0014	0.0018	0.0053	0.0081	0.0112	0.0137	0.0175	0.0210	0.0319	0.0398	5.60
Future_Return	0.0133	0.0114	0.0105	0.0093	0.0102	0.0097	0.0088	0.0093	0.0089	0.0078	−0.0056	−0.83
Panel B: Call Option Turnover												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	***Diff***	***t*-Stat**
VS	−0.0060	−0.0068	−0.0070	−0.0071	−0.0075	−0.0077	−0.0079	−0.0081	−0.0083	−0.0092	−0.0032	−6.18
IV_Skew	0.0500	0.0458	0.0452	0.0443	0.0444	0.0443	0.0440	0.0435	0.0454	0.0472	−0.0028	−0.83
Smirk_C_OA	0.0038	0.0056	0.0060	0.0073	0.0076	0.0082	0.0086	0.0088	0.0085	0.0086	0.0048	2.22
Smirk_C_OI	0.0313	0.0327	0.0337	0.0335	0.0340	0.0344	0.0354	0.0358	0.0371	0.0379	0.0065	1.88
Smirk_P_OA	−0.0323	−0.0352	−0.0355	−0.0343	−0.0343	−0.0346	−0.0351	−0.0344	−0.0356	−0.0352	−0.0029	−0.96
Smirk_P_OI	−0.0249	−0.0286	−0.0279	−0.0312	−0.0321	−0.0331	−0.0336	−0.0345	−0.0355	−0.0344	−0.0095	−2.88
Return	−0.0140	−0.0065	−0.0024	0.0014	0.0059	0.0097	0.0147	0.0203	0.0273	0.0450	0.0590	8.49
Future_Return	0.0128	0.0105	0.0099	0.0095	0.0110	0.0102	0.0094	0.0087	0.0089	0.0081	−0.0047	−0.69
Panel C: Put Option Turnover												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	***Diff***	***t*-Stat**
VS	−0.0055	−0.0070	−0.0073	−0.0077	−0.0076	−0.0077	−0.0079	−0.0081	−0.0084	−0.0082	−0.0027	−5.27
IV_Skew	0.0428	0.0456	0.0437	0.0437	0.0425	0.0425	0.0435	0.0448	0.0472	0.0502	0.0074	2.44
Smirk_C_OA	0.0005	0.0041	0.0054	0.0069	0.0074	0.0081	0.0082	0.0095	0.0103	0.0102	0.0097	5.34
Smirk_C_OI	0.0293	0.0321	0.0325	0.0326	0.0337	0.0345	0.0354	0.0363	0.0382	0.0404	0.0111	3.77
Smirk_P_OA	−0.0360	−0.0343	−0.0330	−0.0332	−0.0330	−0.0341	−0.0342	−0.0356	−0.0363	−0.0380	−0.0020	−0.71
Smirk_P_OI	−0.0268	−0.0285	−0.0288	−0.0298	−0.0307	−0.0322	−0.0329	−0.0343	−0.0351	−0.0386	−0.0118	−3.01
Return	0.0081	0.0110	0.0130	0.0119	0.0110	0.0128	0.0128	0.0087	0.0067	0.0051	−0.0029	−0.43
Future_Return	0.0128	0.0117	0.0105	0.0112	0.0095	0.0091	0.0086	0.0090	0.0085	0.0081	−0.0048	−0.72
Panel D: O/S Ratio (in the Number of Shares)												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	***Diff***	***t*-Stat**
VS	−0.0036	−0.0042	−0.0051	−0.0056	−0.0063	−0.0070	−0.0082	−0.0089	−0.0102	−0.0153	−0.0117	−18.27
IV_Skew	0.0396	0.0429	0.0433	0.0425	0.0428	0.0432	0.0428	0.0432	0.0446	0.0519	0.0123	2.60
Smirk_C_OA	−0.0023	0.0044	0.0043	0.0051	0.0067	0.0069	0.0080	0.0087	0.0093	0.0105	0.0128	4.01
Smirk_C_OI	0.0226	0.0333	0.0304	0.0316	0.0316	0.0324	0.0338	0.0359	0.0380	0.0421	0.0194	4.33
Smirk_P_OA	−0.0251	−0.0334	−0.0361	−0.0312	−0.0335	−0.0337	−0.0338	−0.0343	−0.0352	−0.0383	−0.0132	−2.23
Smirk_P_OI	−0.0266	−0.0215	−0.0237	−0.0282	−0.0285	−0.0302	−0.0315	−0.0338	−0.0356	−0.0384	−0.0118	−2.36
Return	−0.0004	0.0056	0.0076	0.0098	0.0100	0.0106	0.0136	0.0139	0.0147	0.0157	0.0161	2.51
Future_Return	0.0138	0.0119	0.0128	0.0105	0.0104	0.0091	0.0097	0.0085	0.0080	0.0045	−0.0093	−1.43
Panel E: O/S Ratio (in Dollar Value)												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	***Diff***	***t*-Stat**
VS	−0.0043	−0.0045	−0.0049	−0.0056	−0.0060	−0.0064	−0.0073	−0.0083	−0.0091	−0.0186	−0.0144	−17.31
IV_Skew	0.0397	0.0404	0.0400	0.0408	0.0402	0.0412	0.0417	0.0428	0.0455	0.0604	0.0206	4.96
Smirk_C_OA	0.0025	0.0045	0.0060	0.0069	0.0074	0.0083	0.0082	0.0094	0.0090	0.0083	0.0059	3.02
Smirk_C_OI	0.0262	0.0295	0.0291	0.0306	0.0306	0.0328	0.0349	0.0373	0.0391	0.0434	0.0172	4.59
Smirk_P_OA	−0.0282	−0.0306	−0.0321	−0.0299	−0.0315	−0.0329	−0.0333	−0.0344	−0.0369	−0.0423	−0.0141	−3.29
Smirk_P_OI	−0.0196	−0.0249	−0.0239	−0.0274	−0.0289	−0.0303	−0.0331	−0.0355	−0.0367	−0.0376	−0.0179	−4.03
Return	0.0024	0.0052	0.0072	0.0096	0.0110	0.0109	0.0129	0.0135	0.0154	0.0128	0.0105	1.42
Future_Return	0.0123	0.0099	0.0112	0.0118	0.0109	0.0094	0.0095	0.0108	0.0085	0.0049	−0.0074	−1.07

This table summarizes the price discrepancy measures across ten portfolios sorted by trading activities, where the portfolios with larger numbers represent more frequently traded firms. For example, portfolio 9 includes the sample firms whose average option turnovers fall within the top decile. All of the numbers are the averages of the corresponding variable over time. Each panel includes the analysis using a specific trading activity measure. Option turnovers are trading volumes over open interests. O/S ratios are option trading volumes relative to trading volumes of the underlying equity. Diff is the difference between portfolio 0 and portfolio 9. VS is the weighted average difference in implied volatility between paired call and put options with the same strike price, as in Cremers and Weinbaum (2010). IV_Skew is the weighted average difference in implied volatility between OTM and ATM put options, as in Xing et al. (2010). Smirk_C_OA is the difference in implied volatility between ATM call options and OTM call options. Smirk_C_OI is the difference in implied volatility between ITM and OTM call options. Smirk_P_OA is the difference in implied volatility between ATM and OTM put options. Smirk_C_OA is the difference in implied volatility between ITM and OTM put options. Paired differences are used to derive *t*-statistics.

In addition to volatility spread, we also find a pattern suggesting that option traders tend to be more active in trading stocks with better performance during the same time span. We find this by examining the Return variable, which is the monthly return during the month in which firms are sorted based on trading turnover. The above phenomenon is especially prominent for the trading of call options. In both Panels A and B, the difference in concurrent returns between the highest trading turnover decile and the lowest one is statistically significant, with the portfolio with the highest trading turnover earning better return than the one with the lowest trading turnover. This phenomenon suggests that option traders tend to chase "hot" firms in the options market.

According to the above findings, one can conclude that option traders are more active when the volatility spread is low and the underlying stock performs well. However, the subsequent returns on the portfolios with more active trading activities are not any better. Future_Return is the raw monthly return for the same portfolio over the subsequent calendar month; it shows a decreasing trend from the lowest trading decile to the highest one. However, the difference between the top and bottom deciles is not statistically significant.

As discussed above, the pattern of more active trading associated with better concurrent equity returns is mainly driven by call-option traders. The pattern appears in Panels A (all options) and B (call options), but not in Panel C (put options). Two implications may be derived from this finding. First, it is consistent with the general expectation that put options are used for hedging, and therefore, the trading activities of put options are not correlated with recent equity performance. Second, it supports the investor overconfidence hypothesis, in that call option traders are more active when the underlying equities are performing well on average. Note that our analysis here differs from Chen and Sabherwal (2019), as we are examining the characteristics of heavily traded options.

A positive relationship between trading turnover and underlying stock returns is less likely because of informed trading. Given that the short sale constraint is more of an issue in the equity market, investors who hold private information and expect future performance of certain stocks to be bad should tend to take advantage of their private information in the put-options market.

The above does not appear to be the case, however. It is rather difficult to argue that this finding captures investors' accurate forecasts if this pattern only applies to call option trading. If call options are being used for momentum or contrarian strategies, the pattern is inconsistent with the negative (but insignificant) relationship between trading turnover and future returns. Consequently, this finding makes investor overconfidence a more plausible explanation.

Another candidate explanation is the disposition effect. If investors tend to hold on to their losing stakes while liquidating winning ones, the supply of in-the-money options may increase, while that of out-of-the-money options decreases. The phenomenon should lead to less-expensive ITM call options and more-expensive OTM call options. Again, this does not appear to be the case, as Smirk_C_OA and Smirk_C_OI are positively correlated with trading turnover. These two variables measure the relative expensiveness between ATM/ITM options and OTM options, and larger figures mean more expensive ATM/ITM options relative to OTM ones. Therefore, the figures show that heavily traded call options generally have more expensive ATM/ITM options than OTM options. This is not consistent with the disposition-effect hypothesis.

It is worth noting that put option turnover and O/S ratio are positively correlated with implied volatility skew (IV_Skew), which is consistent with the argument that investors tend to utilize out-of-the-money put options to protect their investments in the underlying equity market and therefore make OTM put options more expensive.

Although this study does not rebalance portfolios in a way similar to Cremers and Weinbaum (2010) and Xing et al. (2010), we do consider trading activity and future stock performance. Panels A, B, and C do not show any significant patterns in future stock returns, despite the significant pattern found in volatility spread (VS). Nevertheless, Panels D and E, which use the O/S ratio to capture option trading activities, show some predictability of future equity performance. In Panel D, the O/S ratio is based on the number of shares. It is negatively and significantly correlated with VS, and also negatively correlated with future stock returns. These findings suggest that when the options market is more active than its underlying equity market, the underlying equity tends to have worse performance in the future. This result is consistent with Cremers and Weinbaum (2010) and Xing et al. (2010). However, the direct connection between the O/S ratio and future equity returns may suggest that the options market reveals better information than does the underlying equity market. In addition, although we still find that option investors tend to pursue stocks with higher concurrent returns, this tendency is not as strong as in Panel B. In Panel E, the O/S ratio is based on the USD value of shares. Panel E shows the same pattern as Panel D.

The O/S ratio can be considered a measure of the focus of investors on the options market relative to the equity market, where a higher O/S ratio means more focus on the options market. Since a more active options market predicts worse future equity returns, we may conclude from our findings above that the options market reacts faster to negative signals. This is not inconsistent with the observations from Panels A through C that option traders might have difficulty processing positive signals as indicated by stronger recent performance.

Two potential factors could be driving the findings above, namely, underlying risks and liquidity. To examine whether these factors explain the findings above, Table 7 has analysis similar to that of Table 6, but controls for the above factors. We first ran time-series regressions of option turnovers and O/S ratios against the return volatility of the underlying equity, the proportional effective spread of options, and the illiquidity measure proposed by Amihud (2002) for each sample firm, and then extracted residuals from the regressions. According to Gopalan et al. (2012), this measure is highly skewed, and they use its square root version (p. 342). We also used the same adjusted measure. Then we sorted the sample into deciles according to the excess trading activities captured by OLS residuals.

Table 7. Cross-sectional analyses—excess trading activities against price discrepancy measures.

Panel A: All Option Turnover												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Diff**	***t*-Stat**
VS	−0.0065	−0.0065	−0.0065	−0.0066	−0.0065	−0.0066	−0.0067	−0.0068	−0.0070	−0.0073	−0.0008	−1.75
IV_SKEW	0.0432	0.0418	0.0427	0.0416	0.0414	0.0423	0.0418	0.0416	0.0427	0.0450	0.0017	0.67
SMIRK_C_OA	0.0104	0.0092	0.0089	0.0097	0.0092	0.0089	0.0089	0.0092	0.0090	0.0086	−0.0018	−1.11
SMIRK_C_OI	0.0366	0.0357	0.0367	0.0357	0.0353	0.0359	0.0359	0.0351	0.0366	0.0371	0.0005	0.17
SMIRK_P_OA	−0.0340	−0.0330	−0.0352	−0.0338	−0.0341	−0.0346	−0.0343	−0.0337	−0.0343	−0.0354	−0.0014	−0.63
SMIRK_P_OI	−0.0327	−0.0348	−0.0346	−0.0345	−0.0354	−0.0339	−0.0342	−0.0338	−0.0340	−0.0330	−0.0003	−0.09
Return	0.0083	0.0067	0.0057	0.0082	0.0085	0.0085	0.0125	0.0149	0.0169	0.0237	0.0154	2.30
Future_Return	0.0130	0.0116	0.0101	0.0117	0.0109	0.0122	0.0105	0.0101	0.0118	0.0102	−0.0028	−0.45
Panel B: Call Option Turnover												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Diff**	***t*-Stat**
VS	−0.0066	−0.0067	−0.0067	−0.0064	−0.0067	−0.0065	−0.0066	−0.0066	−0.0070	−0.0072	−0.0006	−1.30
IV_SKEW	0.0419	0.0432	0.0413	0.0428	0.0431	0.0424	0.0417	0.0423	0.0426	0.0434	0.0015	0.61
SMIRK_C_OA	0.0107	0.0098	0.0099	0.0092	0.0096	0.0092	0.0087	0.0088	0.0084	0.0082	−0.0026	−1.63
SMIRK_C_OI	0.0369	0.0355	0.0361	0.0356	0.0366	0.0364	0.0362	0.0358	0.0359	0.0359	−0.0010	−0.31
SMIRK_P_OA	−0.0327	−0.0338	−0.0341	−0.0344	−0.0354	−0.0354	−0.0346	−0.0342	−0.0342	−0.0339	−0.0012	−0.54
SMIRK_P_OI	−0.0328	−0.0324	−0.0345	−0.0353	−0.0353	−0.0353	−0.0347	−0.0339	−0.0343	−0.0316	0.0012	0.34
Return	0.0057	0.0041	0.0050	0.0051	0.0057	0.0085	0.0126	0.0135	0.0224	0.0316	0.0259	3.99
Future_Return	0.0129	0.0108	0.0110	0.0099	0.0111	0.0117	0.0117	0.0102	0.0132	0.0096	−0.0033	−0.55

Table 7. *Cont.*

Panel C: Put Option Turnover												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Diff**	***t*-Stat**
VS	−0.0054	−0.0067	−0.0066	−0.0068	−0.0068	−0.0068	−0.0067	−0.0073	−0.0071	−0.0072	−0.0018	−5.13
IV_SKEW	0.0460	0.0433	0.0417	0.0416	0.0410	0.0406	0.0411	0.0413	0.0430	0.0468	0.0008	1.18
SMIRK_C_OA	0.0078	0.0088	0.0085	0.0084	0.0087	0.0091	0.0095	0.0102	0.0098	0.0106	0.0028	2.20
SMIRK_C_OI	0.0345	0.0358	0.0355	0.0346	0.0359	0.0355	0.0360	0.0362	0.0368	0.0390	0.0045	1.93
SMIRK_P_OA	−0.0354	−0.0349	−0.0336	−0.0336	−0.0337	−0.0331	−0.0339	−0.0337	−0.0350	−0.0369	−0.0015	−0.67
SMIRK_P_OI	−0.0330	−0.0334	−0.0348	−0.0338	−0.0347	−0.0341	−0.0343	−0.0339	−0.0332	−0.0358	−0.0028	−0.62
Return	0.0159	0.0174	0.0149	0.0132	0.0122	0.0132	0.0077	0.0098	0.0047	0.0035	−0.0124	−1.84
Future_Return	0.0143	0.0131	0.0107	0.0120	0.0112	0.0094	0.0098	0.0102	0.0102	0.0107	−0.0037	−0.59
Panel D: O/S Ratio (in the Number of Shares)												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Diff**	***t*-Stat**
VS	−0.0075	−0.0063	−0.0056	−0.0057	−0.0050	−0.0055	−0.0061	−0.0068	−0.0073	−0.0111	−0.0035	−6.84
IV_SKEW	0.0387	0.0391	0.0381	0.0406	0.0410	0.0434	0.0429	0.0448	0.0450	0.0495	0.0108	4.35
SMIRK_C_OA	0.0108	0.0098	0.0090	0.0091	0.0076	0.0083	0.0077	0.0085	0.0095	0.0100	−0.0008	−0.52
SMIRK_C_OI	0.0364	0.0348	0.0350	0.0348	0.0344	0.0336	0.0334	0.0355	0.0379	0.0411	0.0047	1.41
SMIRK_P_OA	−0.0317	−0.0316	−0.0312	−0.0332	−0.0337	−0.0347	−0.0344	−0.0362	−0.0367	−0.0392	−0.0075	−3.38
SMIRK_P_OI	−0.0341	−0.0336	−0.0319	−0.0317	−0.0340	−0.0322	−0.0333	−0.0331	−0.0363	−0.0387	−0.0046	−1.47
Return	0.0125	0.0135	0.0098	0.0087	0.0078	0.0097	0.0109	0.0121	0.0130	0.0157	0.0031	0.49
Future_Return	0.0136	0.0134	0.0133	0.0120	0.0116	0.0096	0.0088	0.0095	0.0087	0.0117	−0.0019	−0.29
Panel E: O/S Ratio (in USD Value)												
Variables	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Diff**	***t*-Stat**
VS	−0.0082	−0.0064	−0.0058	−0.0055	−0.0049	−0.0051	−0.0058	−0.0063	−0.0072	−0.0117	−0.0035	−5.44
IV_SKEW	0.0414	0.0391	0.0388	0.0395	0.0397	0.0405	0.0421	0.0429	0.0442	0.0530	0.0116	4.23
SMIRK_C_OA	0.0105	0.0092	0.0096	0.0093	0.0091	0.0081	0.0075	0.0081	0.0093	0.0098	−0.0007	−0.44
SMIRK_C_OI	0.0376	0.0355	0.0345	0.0337	0.0339	0.0317	0.0333	0.0353	0.0382	0.0427	0.0050	1.40
SMIRK_P_OA	−0.0341	−0.0314	−0.0323	−0.0326	−0.0324	−0.0324	−0.0324	−0.0346	−0.0369	−0.0414	−0.0072	−2.98
SMIRK_P_OI	−0.0359	−0.0347	−0.0341	−0.0328	−0.0318	−0.0298	−0.0315	−0.0329	−0.0355	−0.0386	−0.0027	−0.78
Return	0.0161	0.0123	0.0102	0.0098	0.0094	0.0086	0.0107	0.0122	0.0123	0.0121	−0.0039	−0.52
Future_Return	0.0140	0.0126	0.0126	0.0113	0.0108	0.0096	0.0092	0.0102	0.0101	0.0116	−0.0024	−0.35

This table summarizes the price discrepancy measures across ten portfolios sorted by excess trading activities while controlling for stock return volatility, proportional effective spread of options, and effective spread of underlying equity. The portfolios with large numbers represent firms with more excess-trading activities. For example, portfolio 9 includes the sample firms whose excess option trading measures fall in the top decile in the sample. All of the numbers are the averages of the corresponding variable over time. Each panel includes the analysis using a specific trading activity measure. Option turnovers are trading volumes over open interests. O/S ratios are option trading volumes relative to trading volumes of the underlying equity. Diff is the difference between portfolio 0 and portfolio 9. Paired differences are used to derive *t*-statistics.

At first sight, all five measures have less explanatory power cross-sectionally, except for volatility spread. Again, O/S ratios are positively correlated with volatility skew. However, the statistical significance is consumed by the control variables. It is intuitive to argue that the shift from the equity market to the options market is due to liquidity in corresponding markets, especially when it comes to the processing of negative information. Again, pricing negative information more efficiently in the equity market than in the options market might be relatively tricky. The illiquidity measures in both markets may well account for the difference and therefore consume the predictability. However, the finding that call option traders pursue "hot" stocks but do not predict future performance in the underlying equity market remains intact despite less-significant results.

In sum, Tables 6 and 7 generally support the investor overconfidence hypothesis. Although we also find some evidence supporting informed trading, it is more likely to be due to greater liquidity in the options market relative to the underlying equity market.

To further investigate the role of liquidity in options trading, we performed a double sorting by trading activities and liquidity in Table 8. The model in Easley et al. (1998) suggests that informed traders are more likely to trade in the options market when the liquidity of the options market is high.

Table 8. Cross-sectional analyses—double sorting by trading activities and liquidity measure.

Panel A: Option Turnover as Trading Measure								
1: Volatility Spread		**Option Turnover**						
		1	**2**	**3**	**4**	**5**	**Diff**	***t*-Stat**
Illiquidity	**1**	−0.0046	−0.0050	−0.0058	−0.0055	−0.0074	−0.0028	−3.15
	2	−0.0072	−0.0072	−0.0074	−0.0076	−0.0078	−0.0005	−0.86
	3	−0.0074	−0.0082	−0.0085	−0.0086	−0.0095	−0.0022	−3.42
	4	−0.0073	−0.0080	−0.0080	−0.0089	−0.0095	−0.0022	−4.16
	5	−0.0088	−0.0077	−0.0074	−0.0080	−0.0090	−0.0002	−0.18
	Diff	−0.0042	−0.0027	−0.0017	−0.0025	−0.0016		
	***t*-Stat**	−4.40	−4.46	−3.14	−4.39	−1.98		
2: Volatility Skew		**Option Turnover**						
		1	**2**	**3**	**4**	**5**	**Diff**	***t*-Stat**
Illiquidity	**1**	0.0585	0.0622	0.0567	0.0581	0.0676	0.0090	1.36
	2	0.0512	0.0489	0.0485	0.0498	0.0544	0.0031	0.92
	3	0.0428	0.0454	0.0457	0.0465	0.0499	0.0072	2.57
	4	0.0436	0.0413	0.0414	0.0432	0.0466	0.0030	1.10
	5	0.0401	0.0382	0.0380	0.0395	0.0427	0.0026	1.04
	Diff	−0.0185	−0.0240	−0.0187	−0.0186	−0.0249		
	***t*-Stat**	−3.73	−6.83	−4.35	−4.05	−4.88		
3: Call Volatility Smirk (ATM–OTM)		**Option Turnover**						
		1	**2**	**3**	**4**	**5**	**Diff**	***t*-Stat**
Illiquidity	**1**	−0.0096	−0.0053	−0.0046	−0.0055	−0.0040	0.0056	1.40
	2	0.0035	0.0021	0.0020	0.0018	−0.0001	−0.0036	−1.87
	3	0.0055	0.0077	0.0077	0.0071	0.0057	0.0002	0.11
	4	0.0079	0.0102	0.0106	0.0107	0.0102	0.0023	1.38
	5	0.0126	0.0129	0.0128	0.0132	0.0144	0.0018	1.07
	Diff	0.0222	0.0182	0.0174	0.0187	0.0184		
	***t*-Stat**	6.43	7.79	7.03	8.11	6.92		
4: Call Volatility Smirk (ITM–OTM)		**Option Turnover**						
		1	**2**	**3**	**4**	**5**	**Diff**	**t-Stat**
Illiquidity	**1**	0.0311	0.0274	0.0245	0.0284	0.0338	0.0027	0.60
	2	0.0310	0.0312	0.0280	0.0298	0.0302	−0.0009	−0.28
	3	0.0318	0.0324	0.0332	0.0333	0.0328	0.0010	0.34
	4	0.0369	0.0342	0.0358	0.0360	0.0380	0.0011	0.33
	5	0.0363	0.0370	0.0381	0.0404	0.0437	0.0075	2.08
	Diff	0.0052	0.0096	0.0136	0.0120	0.0100		
	***t*-Stat**	1.37	2.99	3.91	3.16	2.31		
5: Put Volatility Smirk (ATM–OTM)		**Option Turnover**						
		1	**2**	**3**	**4**	**5**	**Diff**	***t*-Stat**
Illiquidity	**1**	−0.0402	−0.0431	−0.0398	−0.0514	−0.0468	−0.0066	−1.02
	2	−0.0361	−0.0353	−0.0364	−0.0379	−0.0397	−0.0035	−1.18
	3	−0.0343	−0.0351	−0.0346	−0.0345	−0.0363	−0.0020	−0.85
	4	−0.0357	−0.0330	−0.0332	−0.0327	−0.0357	0.0000	0.01
	5	−0.0306	−0.0311	−0.0319	−0.0325	−0.0349	−0.0044	−1.70
	Diff	0.0096	0.0121	0.0080	0.0189	0.0118		
	***t*-Stat**	1.81	3.67	2.03	4.48	2.66		

Table 8. *Cont.*

6: Put Volatility Smirk (ITM–OTM)		Option Turnover						
		1	2	3	4	5	Diff	t-Stat
Illiquidity	1	−0.0207	−0.0184	−0.0232	−0.0278	−0.0275	−0.0069	−0.82
	2	−0.0226	−0.0247	−0.0229	−0.0242	−0.0195	0.0031	0.61
	3	−0.0281	−0.0279	−0.0302	−0.0301	−0.0290	−0.0009	−0.32
	4	−0.0364	−0.0328	−0.0337	−0.0332	−0.0353	0.0011	3.42
	5	−0.0370	−0.0344	−0.0363	−0.0396	−0.0427	−0.0057	−1.47
	Diff	−0.0163	−0.0160	−0.0132	−0.0118	−0.0151		
	t-Stat	−2.45	−3.98	−2.63	−1.97	−2.39		
Panel B: O/S Ratio as Trading Measure								
1: Volatility Spread		O/S Ratio						
		1	2	3	4	5	Diff	t-Stat
Illiquidity	1	−0.0032	−0.0048	−0.0067	−0.0121	−0.0211	−0.0179	−7.99
	2	−0.0046	−0.0053	−0.0071	−0.0105	−0.0200	−0.0155	−12.96
	3	−0.0044	−0.0055	−0.0068	−0.0097	−0.0186	−0.0142	−13.62
	4	−0.0044	−0.0056	−0.0067	−0.0081	−0.0141	−0.0097	−12.85
	5	−0.0042	−0.0059	−0.0066	−0.0075	−0.0100	−0.0058	−4.74
	Diff	−0.0010	−0.0011	0.0001	0.0045	0.0111		
	t-Stat	−0.86	−1.94	0.18	4.48	4.96		
2: Volatility Skew		O/S Ratio						
		1	2	3	4	5	Diff	t-Stat
Illiquidity	1	0.0541	0.0510	0.0606	0.0660	0.0878	0.0337	4.44
	2	0.0446	0.0446	0.0476	0.0530	0.0652	0.0206	5.11
	3	0.0410	0.0438	0.0428	0.0454	0.0586	0.0176	4.17
	4	0.0370	0.0378	0.0398	0.0416	0.0498	0.0128	2.88
	5	0.0300	0.0365	0.0360	0.0378	0.0425	0.0125	2.31
	Diff	−0.0241	−0.0145	−0.0246	−0.0282	−0.0453		
	t-Stat	−3.58	−3.69	−7.55	−5.53	−7.01		
3: Call Volatility Smirk (ATM–OTM)		O/S Ratio						
		1	2	3	4	5	Diff	t-Stat
Illiquidity	1	−0.0048	−0.0025	−0.0024	−0.0060	−0.0195	−0.0147	−2.89
	2	0.0033	0.0029	0.0022	0.0026	−0.0014	−0.0046	−2.02
	3	0.0071	0.0068	0.0074	0.0073	0.0051	−0.0020	−0.94
	4	0.0084	0.0088	0.0099	0.0107	0.0104	0.0019	0.98
	5	0.0066	0.0095	0.0120	0.0124	0.0145	0.0079	1.14
	Diff	0.0114	0.0120	0.0145	0.0184	0.0340		
	t-Stat	1.50	4.09	6.42	6.45	8.66		
4: Call Volatility Smirk (ITM–OTM)		O/S Ratio						
		1	2	3	4	5	Diff	t-Stat
Illiquidity	1	0.0340	0.0291	0.0308	0.0283	0.0285	−0.0055	−0.89
	2	0.0271	0.0305	0.0298	0.0305	0.0283	0.0013	0.38
	3	0.0291	0.0302	0.0321	0.0341	0.0337	0.0045	1.26
	4	0.0337	0.0321	0.0340	0.0362	0.0392	0.0055	1.48
	5	0.0332	0.0315	0.0321	0.0370	0.0444	0.0113	1.25
	Diff	−0.0008	0.0023	0.0014	0.0087	0.0160		
	t-Stat	−0.09	0.77	0.42	2.24	2.81		

Table 8. *Cont.*

5: Put Volatility Smirk (ATM–OTM)		O/S Ratio						
		1	**2**	**3**	**4**	**5**	**Diff**	***t*-Stat**
Illiquidity	**1**	−0.0370	−0.0490	−0.0459	−0.0433	−0.0419	−0.0049	−0.63
	2	−0.0369	−0.0356	−0.0372	−0.0365	−0.0406	−0.0037	−0.94
	3	−0.0319	−0.0327	−0.0339	−0.0360	−0.0371	−0.0052	−1.48
	4	−0.0282	−0.0285	−0.0310	−0.0337	−0.0366	−0.0083	−2.19
	5	−0.0255	−0.0290	−0.0276	−0.0306	−0.0355	−0.0100	−2.39
	Diff	0.0115	0.0200	0.0184	0.0127	0.0064		
	***t*-Stat**	1.87	4.45	5.11	2.75	0.99		
6: Put Volatility Smirk (ITM–OTM)		**O/S Ratio**						
		1	**2**	**3**	**4**	**5**	**Diff**	***t*-Stat**
Illiquidity	**1**	−0.0272	−0.0269	−0.0259	−0.0179	−0.0047	0.0225	2.36
	2	−0.0257	−0.0265	−0.0251	−0.0228	−0.0176	0.0082	1.58
	3	−0.0245	−0.0276	−0.0283	−0.0313	−0.0268	−0.0023	−0.52
	4	−0.0378	−0.0278	−0.0315	−0.0345	−0.0357	0.0021	0.43
	5	−0.0131	−0.0298	−0.0311	−0.0360	−0.0429	−0.0298	−3.10
	Diff	0.0141	−0.0029	−0.0052	−0.0181	−0.0382		
	***t*-Stat**	1.29	−0.69	−1.10	−3.35	−4.77		

This table summarizes the price discrepancy measures across 25 portfolios sorted independently by trading activities and liquidity, where the portfolios with larger numbers represent more-frequently-traded and more illiquid firms. For example, Portfolio 5, 5 includes the sample firms whose average option turnovers fall in the top quintile and whose options are the least liquid in the sample. All of the numbers are the averages of the corresponding variable over time. Each panel concludes the analysis using a specific trading activity measure. Option turnovers are trading volumes over open interests. O/S ratios are relative option trading volumes over trading volumes of the underlying equity. Proportional effective spread is used as the liquidity measure. Diff is the difference between Portfolio 1 and Portfolio 5. Paired differences are used to derive *t*-statistics.

Interestingly, after controlling for liquidity, option turnover only explains differences in volatility spread, and only to a much lower degree in volatility smirk. On the other hand, we find that options with higher liquidity tend to have a higher volatility spread and higher volatility skew. It is widely accepted that informed traders may actively trade on put options due to short-sale constraints in the equity market. The finding that higher volatility skew is associated with higher liquidity in both Panels A and B supports the argument. It is somewhat confusing to see a positive correlation between liquidity and volatility spread, controlling for option turnover, as volatility spread and volatility skew predict the opposite direction of future stock returns. In Panel B, when the O/S ratio is used as a trading measure, the results from volatility spread and volatility skew reconcile, especially for firms with more heavily traded options. This finding is consistent with Roll et al. (2010), who argue that O/S indicates informed trading. It is even more interesting to see the relative expensiveness of ATM and OTM call options in Panel B. OTM call options are more expensive for firms with higher O/S ratios and more liquid options. Consistent with the investor overconfidence theory, OTM call options become more expensive when overconfident agents create higher demand for them.

4.3. Momentum and Contrarain Strategies

Some may argue that an explanation for our above findings is that investors are conducting momentum or contrarian strategies in the options market. To further investigate this possibility, we sorted the sample into deciles based on the past one month's return on the underlying equity. If momentum or contrarian strategies are the main driving forces, we should observe a tendency in which the top and bottom deciles exhibit more activity, while the middle deciles are less active. In other words, the trading activities should present a U-shaped pattern across deciles.

We found that the above pattern exists, as described in Table 9. All five turnover measures (TO_O, TO_C, TO_P, OS, and DOS) exhibit similar patterns, especially OS. In addition, the current month's return and the one-month forward return reverse from the previous month. That is, the top performers have lower average rates of returns in the following two months, while the bottom performers have higher average rates of returns.

Table 9. Momentum Portfolios.

Variable	0	1	2	3	4	5	6	7	8	9	Diff	*t*-Stat
VS	−0.0073	−0.0065	−0.0067	−0.0068	−0.0070	−0.0070	−0.0071	−0.0076	−0.0083	−0.0116	−0.0043	−6.07
IV_SKEW	0.0551	0.0463	0.0438	0.0418	0.0422	0.0417	0.0424	0.0415	0.0430	0.0505	−0.0045	−1.54
IV_SMIRK_C_OA	0.0045	0.0071	0.0078	0.0084	0.0083	0.0085	0.0088	0.0086	0.0090	0.0075	0.0030	1.69
IV_SMIRK_C_OI	0.0400	0.0362	0.0349	0.0343	0.0343	0.0343	0.0340	0.0342	0.0344	0.0355	−0.0044	−1.26
IV_SMIRK_P_OA	−0.0435	−0.0368	−0.0348	−0.0326	−0.0331	−0.0324	−0.0322	−0.0324	−0.0335	−0.0372	0.0062	2.55
IV_SMIRK_P_OI	−0.0357	−0.0328	−0.0307	−0.0308	−0.0321	−0.0309	−0.0323	−0.0330	−0.0336	−0.0353	0.0004	0.11
Return	0.0121	0.0128	0.0107	0.0104	0.0106	0.0103	0.0105	0.0072	0.0077	0.0085	−0.0036	−0.42
Future_Return	0.0138	0.0127	0.0120	0.0118	0.0100	0.0088	0.0091	0.0068	0.0067	0.0076	−0.0062	−0.73
TO_O	3.6789	3.7161	3.6557	3.6003	3.6092	3.6525	3.7487	3.9153	4.0726	4.5460	0.8671	9.63
TO_C	3.8779	3.8660	3.7970	3.8022	3.8743	3.9382	4.0091	4.2475	4.4557	4.9205	1.0426	6.76
TO_P	3.7581	3.7082	3.7853	3.6492	3.5696	3.5657	3.5870	3.7105	3.8437	4.2072	0.4492	4.59
OS	0.0754	0.0709	0.0671	0.0674	0.0657	0.0693	0.0691	0.0732	0.0776	0.0901	0.0147	5.38
DOS	0.0090	0.0058	0.0051	0.0052	0.0046	0.0052	0.0052	0.0054	0.0061	0.0085	−0.0006	−1.43
CP	4.3839	5.2058	5.0695	5.1324	5.6455	5.6580	6.3074	5.9968	5.8670	6.9154	2.5315	3.74
L1RET	−0.1760	−0.0843	−0.0498	−0.0252	−0.0037	0.0167	0.0388	0.0654	0.1037	0.2215	0.3976	37.75

The table shows summary statistics for various variables in each of the momentum portfolios. The sample firms are sorted into ten portfolios based on the past month's rate of return in the underlying stocks. The average past one month return for each portfolio is shown in row L1RET. TO_O, TO_C, and TO_P are option turnovers for all options, call options, and put options, respectively, and are defined as trading volume over open interest. O/S ratios are option trading volumes relative to trading volumes of the underlying equity. OS is based on the number of shares and DOS is based on the USD value of shares. Diff is the difference between portfolio 0 and portfolio 9. VS is the weighted average difference in implied volatility between paired call and put options with the same strike price, as in Cremers and Weinbaum (2010). IV_Skew is the weighted average difference in implied volatility between OTM and ATM put options, as in Xing et al. (2010). Smirk_C_OA is the difference in implied volatility between ATM call options and OTM call options. Smirk_C_OI is the difference in implied volatility between ITM and OTM call options. Smirk_P_OA is the difference in implied volatility between ATM and OTM put options. Smirk_C_OA is the difference in implied volatility between ITM and OTM put options.

While above findings in Table 9 suggest that contrarian strategies may be one of the reasons for the previous findings, the differences between the middle and bottom deciles are trivial. For example, the difference in option turnover (TO_O) between the worst performers (portfolio 0) and the decile with the lowest turnover rate (portfolio 3) is only approximately 0.07. On the other hand, the difference in the same measure between the top performers (portfolio 9) and the worst performers (portfolio 0) is 0.8671, and the difference is statistically significant. This suggests that while momentum or contrarian strategies might be an explanation for the phenomena, their contributions are not substantial. Also, significantly higher trading activities among the past top performers further strengthen the investor overconfidence argument, in that traders are pursuing "hot" stocks but do not seem to succeed much. The subsequent returns show a negative relationship with trading activities, but the relationship does not have statistical support (the differences are not statistically significant).

4.4. Interactions between Options and Stock Markets

Although this paper focuses on the trading activities in the options market and their potential impact on option prices, it is worthwhile to look at the underlying stock market. In the last analysis, OS is the most influential indicator among all trading activity measures. Since many stock market investors also trade in the options market, it is not surprising to see stock-market trading activities correlated with option pricing in certain ways. To examine the extent to which stock trading behaviors affect both option trading and option pricing, we conducted a cross-sectional analysis similar to that in Section 4.2, using both one-way and two-way sorting.

Table 10 summarizes the empirical results. In Panel A, sample firms are sorted into deciles based solely on stock trading turnover, defined as the stock trading volume divided by the number of shares outstanding. By comparing Panel A in Tables 6 and 10, we find similar patterns across all rows. However, there are a few distinctions.

Table 10. Cross-sectional analyses—interactions between stock and options markets.

Panel A: Stock Trading Turnover

Variables	0	1	2	3	4	5	6	7	8	9	Diff	*t*-Stat
VS	−0.0068	−0.0061	−0.0064	−0.0068	−0.0064	−0.0066	−0.0071	−0.0075	−0.0085	−0.0139	−0.0071	−3.31
IV_SKEW	0.0401	0.0384	0.0384	0.0401	0.0411	0.0425	0.0433	0.0451	0.0481	0.0567	0.0166	6.41
SMIRK_C_OA	0.0072	0.0074	0.0080	0.0072	0.0078	0.0075	0.0085	0.0077	0.0079	0.0090	0.0018	1.09
SMIRK_C_OI	0.0288	0.0306	0.0304	0.0288	0.0320	0.0340	0.0344	0.0359	0.0383	0.0448	0.0160	4.77
SMIRK_P_OA	−0.0269	−0.0280	−0.0287	−0.0269	−0.0320	−0.0333	−0.0352	−0.0358	−0.0379	−0.0434	−0.0165	−7.52
SMIRK_P_OI	−0.0233	−0.0266	−0.0281	−0.0233	−0.0314	−0.0316	−0.0324	−0.0331	−0.0357	−0.0411	−0.0178	−5.81
Return	0.0041	0.0068	0.0087	0.0041	0.0103	0.0121	0.0119	0.0119	0.0143	0.0112	0.0072	0.89
Future_Return	0.0085	0.0085	0.0100	0.0085	0.0099	0.0118	0.0099	0.0092	0.0109	0.0107	0.0022	0.30

Panel B: Double Sorting By Stock Turnover and Option Turnover

1: Volatility Spread		Option Turnover						
		1	2	3	4	5	Diff	*t*-Stat
Stock Turnover	1	−0.0057	−0.0066	−0.0068	−0.0065	−0.0069	−0.0012	−1.95
	2	−0.0058	−0.0063	−0.0067	−0.0066	−0.0070	−0.0012	−2.18
	3	−0.0065	−0.0064	−0.0067	−0.0066	−0.0064	0.0000	0.03
	4	−0.0073	−0.0071	−0.0071	−0.0076	−0.0074	0.0000	−0.07
	5	−0.0110	−0.0110	−0.0106	−0.0109	−0.0118	−0.0008	−0.64
	Diff	−0.0053	−0.0044	−0.0038	−0.0044	−0.0049	−0.0061	
	t-Stat	−4.59	−5.55	−6.26	−8.37	−7.44		−10.47

This table summarizes the price discrepancy measures across portfolios sorted by stock market trading activities, where the portfolios with larger numbers represent more frequently traded firms. All of the numbers are the averages of the corresponding variable over time. In Panel A, all the monthly observations are sorted into ten portfolios based on stock trading turnover. In Panel B, they are sorted independently, based on option turnover and stock turnover. Diff is the difference between the most- and least-frequently traded portfolios (portfolio 9–portfolio 0 in single sorting, and portfolio 5–portfolio 1 in double sorting). VS is the weighted average difference in implied volatility between paired call and put options with the same strike price, as in Cremers and Weinbaum (2010). IV_Skew is the weighted average difference in implied volatility between OTM and ATM put options, as in Xing et al. (2010). Smirk_C_OA is the difference in implied volatility between ATM call options and OTM call options. Smirk_C_OI is the difference in implied volatility between ITM and OTM call options. Smirk_P_OA is the difference in implied volatility between ATM and OTM put options. Smirk_C_OA is the difference in implied volatility between ITM and OTM put options. Paired differences are used to derive *t*-statistics.

First, the differences between the most- and least-frequently traded portfolios in all option pricing measures are statistically significant in Table 10, except for the volatility smirk between OTM and ATM call options. In Table 6, the differences in volatility skewness and in volatility smirk between OTM and ATM put options are not statistically significant. Second, the concurrent returns across portfolios increase monotonically with trading frequency in Table 6, but this phenomenon does not appear in Table 10. In addition, the t-test suggests no significant difference in contemporaneous return between the most and the least frequently traded portfolios in Table 10. These findings may be due to the use of momentum or contrarian strategy in the options market. From Table 6, we may attribute this finding more to the momentum traders, as ATM calls tend to be more expensive in the portfolio with more frequent option trading. However, it is less so in Table 10. Instead, a much steeper volatility skew for the most frequently traded portfolio in Table 10 suggests that OTM put options are much more expensive. Looking at Panel B in Table 10, we also find that stocks with less frequent option trading drive the steeper volatility skew. This conflicts with the notion in Xing et al. (2010) that informed traders use OTM put options to take advantage of negative information, but it is more in line with the investor overconfidence hypothesis of the stock market.

5. Discussion

This paper examines the relationship between trading activities and option pricing patterns. If investor overconfidence causes heavier trading activities, the option pricing patterns should strongly correlate with trading activities. Furthermore, market volatility should also be positively correlated with the trading activity. We present evidence showing that both relationships do exist. The relationships hold both over time and cross-sectionally.

The negative relationship between volatility spread and trading activity suggests that options traders are contrarians overall. The supporting evidence is also provided, by sorting the sample into deciles based on past equity returns. However, the findings also suggest that the differences in trading activities and volatility spread and volatility skew do not predict future equity returns.

Our findings in this study differ from those of Cremers and Weinbaum (2010) and Xing et al. (2010) regarding the predictability of volatility spread and volatility skew, and therefore serve as evidence against theories of informed trading or superior information in the options market. Instead, our findings support the investor overconfidence theory in that options traders also tend to pursue top performers, strengthening the argument in Chen and Sabherwal (2019) that the positive relationship between past market return and option trading activities may be due to investor overconfidence.

This study adds to the discussion in the literature regarding the role played by behavioral biases. While the debate between efficient market advocates and behavioral finance supporters is still active in the equity market, this paper extends the debate to the options market. This focus on the options market not only provides insights to market speculators trying to exploit opportunities in the options market, but also serves as a caution to investors who heavily hedge their portfolios in the equity options market. If behavioral biases play an important role in the options market, the effectiveness of using options to hedge equity portfolios might be degraded. This study shows that options traders should pay attention to the behavioral patterns in the options market regardless of their purposes in trading. However, in this study, we focus on the generalized patterns using market-wide data, which may limit our interpretation of the empirical results. While retail investors may exhibit a higher degree of behavioral biases (Choy 2015; Baig et al. 2022; Ülkü et al. 2023), we do not attempt to differentiate between the sources of trading (retail versus institutional) in this study. We leave to future research the enhancement of our understanding of retail investors' role in option trading. Also, this study does not focus on the COVID-19 period, during which retail investor participation played a particularly important role. It would be interesting to examine the role of behavioral biases in the options market exclusively during this period.

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