Implied Volatility Spread and Stock Mispricing

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ABSTRACT

This paper examines the impact of options trading on stock price informativeness. Availing ourselves of the stock mispricing measure proposed by Stambaugh et al. (2015), we show that informed trading in the options market, proxied by the implied volatility spread, can substantially mitigate stock mispricing. Higher implied volatility spread reliably predicts subsequently lower stock mispricing after controlling for an array of economic variables including firm size, illiquidity, idiosyncratic volatility, institutional ownership, and investor's divergence of opinions. In addition, this effect is more pronounced when the options trading volume is higher, consistent with the notion that higher options trading volume provides better camouflage for informed trading in the spirit of Kyle (1985). We further show that a self-financing monthly portfolio that goes long on most underpriced stocks and short on most overpriced stocks *when* the implied volatility spread is the lowest yields statistically and economically significant abnormal returns.

JEL Classifications: G10, G11, G14, G40

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1. Introduction

Whether financial assets are correctly priced or not is of great importance to the long-lasting theme of market efficiency. It is well established in the existing literature that informative stock prices have profound implications on many important issues in corporate finance including corporate investment (Chen et al. (2007), Foucault and Gehrig (2008)), board structure (Ferreira et al. (2011)), cash savings behavior (Fresard (2012)), board's monitoring effort (Gorton et al. (2017)), corporate innovation outcomes (Mathers et al. (2016)), firm productivity (Bennett et al. (2020)). Consequently, it is meaningful and important to examine the determinants of stock price informativeness.

In this paper, we attempt to contribute to this literature by investigating the impact of the options market on stock price informativeness. Availing ourselves of the stock mispricing measure proposed by Stambaugh et al. (2015), we show that informed trading in the options market, proxied by the implied volatility spread, can substantially mitigate stock mispricing. Higher implied volatility spread reliably predicts subsequently lower stock mispricing after controlling for an array of economic variables including firm size, illiquidity, idiosyncratic volatility, institutional ownership, investor's divergence of opinions. In addition, this effect is more pronounced when the options trading volume is higher, consistent with the notion that higher options trading volume provides better camouflage for informed trading in the spirit of Kyle (1985). We further show that a self-financing monthly portfolio that goes long on most underpriced stocks and short on most overpriced stocks when the implied volatility spread is the lowest yields statistically and economically significant abnormal returns.

Our paper adds to the extant literature in three aspects. First, while there has been ample evidence on informed trading in the options market, there has been relatively little research that examines the implications of such trading on the stock price informativeness. By connecting the literature on informed options trading to stock price informativeness, we integrate these two big strands of literature and provide direct evidence on the predictive power of informed options trading. Second, by incorporating economic factors that capture the information environment, the limits of arbitrage, and arbitrage risk, we uncover new evidence on the determinants of stock mispricing. Third, our paper adds new insights to professional money managers by documenting the construction and profitability of an investment strategy that exploits stock mispricing conditional on the implied volatility spread. We show that such a strategy can yield economically and statistically significant abnormal returns.

Our paper is most closely related to Cao et al. (2020), who also examine whether options trading increases the absolute level of information content of prices. Our paper differs from theirs in that we use the stock mispricing measure in the sense of Stambaugh et al. (2015) whereas they resort to transformed R-squareds and idiosyncratic volatility to proxy for stock price informativeness.[1] In addition, they utilize the option trading volume whereas we employ the options implied volatility spread as a proxy for informed trading. The fact that both our paper and theirs find supportive evidence of options trading enhancing stock price informativeness and reducing stock mispricing clearly speaks to the beneficial effects of options trading on the underlying stocks.

The rest of the paper is organized as follows. In Section 2 we review the literature on stock mispricing and informed options trading. We describe the data and methodology used in the empirical analysis. In Section 4 we report the main empirical results. Section 5 concludes.

2. Literature Review

In this section, we survey two big strands of literature: the stock mispricing literature and the options trading literature. Our focus is on how these two strands of literature intersect in a way that allows us to derive testable hypotheses on the implications of options trading on stock mispricing.

2.1. Literature on stock mispricing and stock price informativeness

Traditional financial theory claims that asset prices do not systematically deviate from their fundamental values due to the existence of arbitrageurs who are incentivized to take positions against the price deviations. One underlying assumption of this argument is that arbitrageurs have the ability to quickly eliminate any price deviations and restore equilibrium prices. Thus, any mispricing is only short-lived and cannot persist.

However, recent research has challenged this assumption and championed the notion of limits of arbitrage and arbitrage risk. De Long et al. (1991) advocate the notion of noise trader risk and contend that arbitrageurs cannot correct mispricing caused by such less rational traders. Barberis et al. (1998) and Daniel et al. (1998) argue that investors are subject to various psychological factors and biases such as investor sentiment, overconfidence, and conservatism. Such factors and biases can deter arbitrage activities and lead to persistent mispricing. Theoretical work by Gromb and Vayanos (2002) and Chen et al. (2002) provides insights into why arbitrageurs fail to exploit arbitrage opportunities, therefore allowing mispricing to persist. Pontiff (2006) points out that idiosyncratic risk represents risk for arbitrageurs seeking to exploit mispricing. Doukas et al. (2010) contend that mispricing is a manifestation

[1] It is noteworthy to point out that whether the stock return synchronicity implies more or less informative stock prices is quite controversial. See Li et al. (2020) and the references therein for more details.

of the inability of arbitrageurs to hedge idiosyncratic risk, which serves as a major deterrent to arbitrage activities. They further document that stocks with higher arbitrage risk have higher estimated mispricing than stocks with low arbitrage risk.

A related strand of literature examines the implications of stock price informativeness. It is now widely accepted that whether the stock prices are informative about firms' fundamentals can have material impact on corporate financial decision making. Chen et al. (2007) argue that the amount of private information in stock price has a strong positive effect on the sensitivity of corporate investment to stock price. Foucault and Gehrig (2008) show that cross-listing enables firms to obtain more precise information about their growth opportunities. Thus, such firms have higher sensitivity of investment to stock prices and trade at a premium. Ferreira et al. (2011) find that more informative stock prices have less demanding board structure. Fresard (2012) contend that corporate cash savings are much more sensitive to stock price when the stock price contains more information that is new to managers. De Cesari and Huang-Meier (2015) argue that managers learn from information stock prices and use it to set dividend policy. They find that firms' dividend changes are more strongly related to returns when returns are more informative. Ben-Nasr and Alshwer (2016) examine whether managers use information included in stock prices when making labor investment decisions. They document a positive relationship between labor investment efficiency and stock price informativeness. To the extent that such literature exemplifies the importance of stock price informativeness, we believe they provide a strong justification for our research topic.

2.2. Literature on informed options trading

In the classical Black-Scholes (1973) paradigm, options' payoffs can be replicated by the underlying securities in complete markets and their values derive from the underlying assets. Consequently, options are considered as redundant securities, implying that options trading should convey no new information to the market. However, in the presence of various market frictions, the complete market condition is often violated. As a result, options may no longer be redundant. Moreover, due to high leverages and the power of overcoming the short-sales constraints, options may be viewed as superior investment vehicles. Informed traders may choose to trade options to capitalize on their private information. In this case, price discovery can take place in the options market. Consistent with this argument, Chakravarty, Gulen and Mayhew (2004), among others, document supportive evidence that the options market contributes around 17 percent of the stock price discovery. In this paper, we focus on the possibility that options trading can potentially enhance stock price informativeness and mitigate potential stock mispricing.

As options listing becomes increasingly widespread, recent studies focus on the informational content of options trading. The theoretical work by Easley et al. (1998) lays the economic foundation for informed trading in the options market. Empirical studies have since documented strong supportive evidence for informed options trading around corporate earnings announcements (Amin and Lee (1997), Roll et al, (2010)), immediately before merger and acquisitions announcements (Cao et al. (2005)). Also, by focusing on options trading volume, Pan and Poteshman (2006) present compelling evidence that their constructed put-call ratio predicts future stock returns. Johnson and So (2012) find that the O/S ratio also predicts future firm-specific earnings news, consistent with O/S reflecting private information. Cao et al. (2020) show that options trading increases the information content of stock prices. They contend that higher option trading volume implies higher information acquisition by investors and more information disclosure by managers.

Albeit insightful, using the options trading volume to study the informational content of options trading has its limitations, often requiring either high-frequency data on options trades and quotes or proprietary data to sign the option trading volume. For instance, both Amin and Lee (1997) and Cao et al. (2005) employ the Berkeley Options Database, which covers time-stamped options trades and quotes from 1976 to 1995. In comparison, Pan and Poteshman (2006)'s construction of the put-call ratio requires a proprietary dataset that is not publicly available. In view of this, recent empirical studies have employed the options implied volatility spread to proxy for the informed trading in the options market.

A growing strand of literature has turned to implied volatility spread to infer information about the underlying stock. Implied volatility spread is defined as the difference between call implied volatility and put implied volatility, where call and put options are matched on strike prices and maturities. Under perfect market conditions and for a given strike price and maturity combination, call implied volatility should be the same as the put implied volatility since both of them are measuring the forward-looking volatility of the same underlying stock. Directional move of the underlying stock price, however, can cause significant deviations of the call implied volatility from the put implied volatility. For instance, positive information about the underlying stock can drive up the demand for and the prices of calls as opposed to puts. The relative pricing pressure on calls translates into more expensive calls, and thus higher call implied volatilities. Similarly, negative information induces more expensive puts, leading to higher put implied volatilities.

A few widely cited studies have demonstrated that the implied volatility spread has strong predictive power on the future stock returns. Bali and Hovkimian (2009) demonstrate that the call-put implied volatility spread is indicative of the future price increase of the underlying stock. Xing et al. (2010) examine the predictive power of a variation of volatility spread, i.e., the volatility smirk among a cross section of stocks. They find that stocks with the steepest smirks in their traded options underperform stocks with the least pronounced volatility smirks in their traded options by 10.9 percent on an annual basis after risk adjustment. Cremers and Weinbaum (2010) document that deviations from put-call parity contain information about future stock returns beyond short sales constraints. Stocks with relatively expensive calls (higher call implied volatilities relative to put implied volatilities) outperform stocks with relatively expensive puts by 50 basis points on a weekly basis. Such predictability is robust to firm size and varies with the liquidity of the options and the underlying stock. Lei et al. (2017) show that the volatility spread builds up in the days leading up to the earnings announcement dates and predicts subsequent announcement returns. In this paper, we use the implied volatility spread to examine the impact of options trading on subsequent stock mispricing.

3. Data and Methodologies

We use a number of data sources to conduct our empirical analysis including CRSP, Compustat, OptionMetrics, Thomson Reuters. When constructing our sample, we merge across various databases by using CUSIP as the common firm identifier. We provide more detailed information on the sample construction process below.

3.1. Options data

We obtain options implied volatility data from the Ivy DB OptionMetrics, which has evolved into the standard database for options-related research in the absence of intraday options trades and quotes data. OptionMetrics starts covering equity options from 1996, hence, our sample starts from 1996. For each optioned stock, OptionMetrics provides the end-of-day summary data of options volume, the best bid and best offer prices, contract types (call or put), strike prices and expiration dates. In addition, OptionMetrics provides standardized options price files (stdopd). Such files contain prices, implied volatilities, and Greeks for at-the-forward-money call and put options with fixed days until expiration.[2] The strike prices of these standardized options are set to be equal to the forward price of the underlying stock with the forward delivery date matching the expiration date. OptionMetrics further calculates an implied volatility surface using values interpolated from available options price data. We follow Bali, Engle, and Murray (2016) and use the implied volatility estimates from these standardized options.

We apply a number of filters when extracting the implied volatility data. The option prices, forward prices, and the implied volatilities must be greater than zero; The strike price must equal the forward price of the underlying stock; Call and put options are matched on strike prices and maturities. We take the simple averages of the daily implied volatility spread to construct the monthly series of the implied volatility spread. Our empirical analysis uses standardized options with a maximum maturity of 365 days. Our robustness checks reveal that the results remain qualitatively the same when other maturity cutoffs, such as 30 days, 60 days, or 180 days, are used.

[2] Specifically, standardized option price files have options with 30, 60, 91, 182, 273, 365, 547, and 730 days until expiration.

3.2. Equities data

Existing studies on stock mispricing prompt us to control for several factors that can affect stock mispricing such as limits of arbitrage and arbitrage risk. Specifically, we use CRSP share prices and shares outstanding to calculate the market capitalization. We use stock volume and returns data to calculate Amihud's illiquidity measure as well as the standardized unexplained volume as a proxy for investors' divergence of opinions. We use CRSP daily return files to estimate the idiosyncratic volatility. We use Thomson Reuters holdings data to calculate the institutional ownership. Wherever possible, we have followed the literature and constructed our control variables, details of which are provided in the Appendix.

Our sample period ends in 2016. Table 1 reports the summary statistics of all the variables used in our empirical analysis. We include the key statistics such as the mean, the standard deviation, the 5^{th}, the 25^{th}, median, the 75^{th}, and the 95^{th} percentiles. A total of over 315,629 firm months survives the various kinds of filters in our sample construction process. Table 2 present the correlation structure of select variables.

4. Empirical Results

4.1. Average returns and alphas on portfolios of stocks sorted by MISP and VS

The informed options trading literature documents ample evidence supporting the notion that informed traders may choose to trade options first to profit on their private information. Such informed trading allows new information to find its way into the options prices and eventually the stock prices. As such, new information is registered into asset prices in a timely manner, which will alleviate any potential mispricing. We thus expect that informed options trading can mitigate the stock mispricing.

Given that implied volatility spread proxies for informed trading in the options market, we start with an investigation of the stock mispricing effect under varying degrees of the implied volatility spread. Empirically, we first resort to a double sorting procedure. Every month in our sample, we first sort stocks into ten deciles based on the stock mispricing measure MISP. Within each decile, we further sort stocks into ten deciles based on the implied volatility spread in the previous month. We thus form 100 portfolios using this double sorting procedure. We then examine the returns to the 100 portfolios in the following month.

Our focus is on the returns difference between the most underpriced and overpriced stocks. Insofar as the informed options trading alleviates stock mispricing, we expect the mispricing effect should be most dramatic when informed trading is the weakest. In other words, we expect to see the most pronounced return difference between the underpriced and overpriced stocks when the implied volatility spread is the lowest. In comparison, when informed trading is the strongest, new information is quickly registered into stock prices, thus potentially mitigating, or eliminating any mispricing. Consequently, we expect the least dramatic return difference between underpriced and overpriced stocks when the implied volatility spread is the highest.

Table 3 reports the average returns of the 100 portfolios formed by the double sorting procedure using the stock mispricing MISP and implied volatility spread VS. Panel A and B presents the average returns for the equal-weighting and value-weighting portfolios, respectively. The ten rows correspond to the ten deciles based on the MISP sorting whereas the ten columns correspond to the ten deciles formed by the VS sorting.

We immediately notice that across the ten VS groups, underpriced stocks (MISP Decile 1) on average earn better returns than overpriced stocks (MISP Decile 10) in the following month, thus speaking to the validity of the MISP measure. More importantly, the return difference between MISP decile 1 and MISP decile 10 is far more striking for the bottom VS group than for the top VS group. Under equal-weighting (value-weighting), the return difference in the bottom VS group stands at 1.93% (1.74%) per month with a t-stat of 5.14 (3.45). As a matter of fact, stocks in the MISP Decile 10 and VS Decile 1 are most overpriced in that they earn a return of -0.72% (-0.56%) under equal (value) weighting. In comparison, the return difference in the top VS group is merely 0.07% (0.48%) with a t-stat of 0.15 (0.82).

We further subject the portfolio returns in Table 3 to risk adjustments using the traditional asset pricing models and calculate the abnormal returns to each of the 100 portfolios. Our intention is to examine whether the superior performance of the underpriced stocks relative to the overpriced stocks when the volatility spread is the lowest remains after adjusting for the risks in each portfolio. Table 4 reports the alphas of the 100 portfolios. Similarly, we structure the ten rows for the MISP sorting and the ten columns for VS sorting. Panel A and Panel B presents the alphas under equal (value) weighting.

We observe that the alpha difference between the most underpriced and overpriced stocks exhibits a similar pattern as reported in Table 3. Specifically, the alpha difference between MISP Decile 1 and MISP Decile 10 stands at 2.05% (2.11%) with a t-stat of 5.71 (4.58) for the bottom VS decile. Again, the most overpriced stocks with the lowest implied volatility spread earn an abnormal return of -0.86% (-0.87%) per month. In contrast, such alpha difference is merely 0.38% (0.92%) with a t-stat of 1.03 (1.72) under equal (value) weighting for stocks that have experienced the most heightened implied volatility spread.

Taken together, results in Table 3 and 4 strongly support the notion that the stock mispricing is mainly concentrated among stocks that have the lowest informed options trading. Such mispricing is almost completely eliminated when the stocks have witnessed intensified informed trading in the options market as proxied for by the implied volatility spread.

4.2. Firm-level cross sectional predictive regressions using *VS*

The results in Table 3 and 4 illustrate the significance of the implied volatility spread as one of many factors that can affect stock mispricing. While it is intuitive and informative, it suffers from two big disadvantages: first, it throws away a large amount of information in the cross section since the portfolio-level analysis relies on aggregating the individual stocks. Second, it is difficult to control for multiple return predictors simultaneously at the portfolio level. In this section, we aim to address these two limitations by employing a rigorous regression analysis by controlling for other factors that may affect stock mispricing. Our intention is to examine whether the impact of the implied volatility spread on stock mispricing persists after incorporating such control variables.

We use the Fama and MacBeth (1973) regression framework to conduct the firm-level cross-sectional regressions. Each month in our sample, we run the following cross-sectional regression and nested versions thereof:

$$MISP_{i,t} = \beta_o + \beta_1 VS_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 SUV_{i,t-1} + \beta_4 Illiq_{i,t-1} + \beta_5 IVOL_{i,t-1} + \beta_6 IOR_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

where *MISP* is the stock mispricing measure for stock i in month t. Motivated by extant literature, we include the following control variables: firm size *Size*, investor's divergence of opinions *SUV*, Amihud's illiquidity *Illiq*, idiosyncratic volatility *IVOL*, and institutional ownership *IOR*.

Table 5 presents the time-series averages of the slope coefficients from the regression of stock mispricing on the implied volatility spread and the control variables. We use one-month lagged values of the implied volatility spread and other control variables to predict the stock mispricing. We estimate a total of 6 alternative models. The Newey-West adjusted t-statistics are included in the parentheses. In the last column of Table 5, we report the results for the full specification with *VS* and all control variables.

A few observations are available. First, *Size* carries negative and highly significant coefficient estimates across all the models we have estimated. Thus, larger firms reliably result in less stock mispricing. This is expected given that larger firms are often associated with greater information acquisition and information production. For instance, larger firms typically have more analyst following and analyst coverage. Larger firms also receive wider media coverage. Much higher information acquisition and processing helps faster incorporation of value-relevant information, thus reducing any mispricing. Second, *IVOL* carries strongly significant and positive estimates. Thus, stocks with greater idiosyncratic volatility are subject to more mispricing. This is consistent with the existing literature (Doukas et al. (2010), Stambaugh et al. (2015), Stambaugh et al. (2017)). For stocks with highly idiosyncratic risk, it is difficult to elicit arbitrage activity. Consequently, such stocks are more likely to trade at market prices far from their fundamental values. Higher idiosyncratic volatility limits arbitrage trading and allow stocks to remain mispriced. *IOR* shows up with negative and significant coefficient estimates. Thus, stocks with higher institutional ownership are prone to less mispricing. This is consistent with the notion that institutional investors are more sophisticated than individual investors, and thus, a higher proportion of institutional holding helps faster incorporation of information into stock prices and promote stock price informativeness, leading to less mispricing. Notice that *Illiq* is reliably inversely related with stock mispricing, which contradicts with the notion that more illiquid stocks are hard to arbitrage and hence experience greater mispricing. However, this is consistent with the notion that more liquid stocks allow for greater presence of noise traders, the existence of which can allow for greater mispricing. Further notice that *SUV* shows up with negative and significant estimates. Thus, stocks with greater divergence of opinions witness less mispricing.

Our focal variable is *VS*. Across the six models we have estimated, *VS* always carries negative and highly significant coefficient estimates. Thus, greater implied volatility spread month t leads to less mispricing in month t+1 after controlling for factors that have been documented to affect mispricing. This certainly reinforces the results reported in Table 3 and 4 and strongly supports the notion that heightened informed trading can substantially alleviate mispricing.

4.3. The role of options trading volume

One may wonder the role of options trading volume. Indeed, as we argue in the literature survey section, earlier studies have examined the informational content of options trading volume by looking at high-frequency options trade and quote data or proprietary volume data. To the extent that we cannot sign the direction of options trading volume, the use of options trading volume to proxy for the informational content of options trading is very noisy and can lead to incorrect inferences. However, this does not necessarily imply that we should ignore the options trading volume completely. In this section, we derive an additional set of tests that aim to utilize the options trading volume to further reinforce the impact of implied volatility spread on stock mispricing.

In an influential paper, Kyle (1985) builds a dynamic model to examine informed trading in the presence of noise traders. Kyle (1985) contends that informed traders will trade slowly to prevent their private information from being revealed completely and too quickly. To achieve this, informed traders need to utilize the camouflage provided by the noise traders, since such camouflage will conceal their trading from the market makers. Similarly, Admati and Pfleiderer (1988) develop a theoretical model to explore the implications of the strategic interaction between discretionary liquidity traders and informed traders. One of the main predictions from Admati and Pfleiderer (1988) is that concentrated-trading patterns arise endogenously as a result of the strategic behavior of liquidity traders and informed traders. Empirically, such concentrated trading can explain the U-shaped pattern for intraday trading volume.

We argue that periods of heightened options trading volume are precisely when the camouflage is at its best. Alternatively, such periods can be viewed as the concentration periods in Admati and Pfleiderer (1988). Thus, we expect that in the presence of higher options trading volume, informed traders will trade more aggressively due to better camouflage. Consequently, more informed trading will further reduce any stock mispricing.

To test this hypothesis, we augment the previous regression with an interaction term between VS and option trading volume. Specifically, each month in our sample, we run the following cross-sectional regression and nested versions thereof:

$$\begin{aligned} MISP_{i,t} = {} & \beta_o + \beta_1 VS_{i,t-1} + \beta_2 OptVol_{i,t-1} + \beta_3 VS \cdot OptVolze_{i,t-1} + \beta_4 Size_{i,t-1} + \beta_5 SUV_{i,t-1} \\ & + \beta_6 Illiq_{i,t-1} + \beta_7 IVOL_{i,t-1} + \beta_8 IOR_{i,t-1} + \varepsilon_{i,t} \end{aligned} \quad (2)$$

OptVol is the natural log of the monthly options trading volume. Similar to Chae (2005) and Cao et al. (2020), we use the log transformation on the OptVol variable so that it is closer to the normal distribution.

We include the same set of control variables as in Table 5. Our focal variable is the interaction term between *VS* and *OptVol.* To the extent that higher options trading volume provides better camouflage for informed traders and promote greater informed trading, we expect a negative slope coefficient estimate before *VS* and *OptVol.*

Table 6 presents the time-series averages of the slope coefficients from the regression of stock mispricing on the implied volatility spread and the control variables. Similar to Table 5, we estimate a total of 6 alternative models. The Newey-West adjusted t-statistics are included in the parentheses. In the last column of Table 6, we report the results for the full specification with *VS* and all control variables.

We immediately observe that virtually all the control variables remain statistically significant. For instance, larger firms and firms with greater institutional ownership tend to experience less mispricing. Stocks with greater idiosyncratic volatilities tend to have greater mispricing. *Illiq* remains negative and significant in the full specification (Model 6). More importantly, we notice that the interaction term between *VS* and *OptVol* carries negative coefficient estimates that are highly significant across all the models we have estimated. Interestingly, VS remains negative but insignificant in Model 1 and Model 6. Thus, the predictive power of *VS* is completely absorbed by the interaction term between *VS* and *OptVol.* Overall, results in Table 6 lend strong support the notion that heightened options trading volume facilitates greater informed trading, which further leads to less mispricing.

4.4. Profitability of long/short strategies based on MISP augmented with VS

Results in Table 3, 4 and 5 suggest that it is possible to construct a compound strategy that incorporates the predictive power of both MISP and VS to capture the striking return difference between low and high MISP stocks for bottom VS decile stocks. We label this strategy as the compound strategy since it originates from the predictive power of two return predictors: MISP and VS. In the following, we document the construction of the compound strategy and report its returns and alphas.

To form the portfolios, we again conduct the double sorting procedure. Each month in the sample, stocks are first sorted into ten deciles based on the mispricing measure MISP. Within each decile, stocks are further sorted into ten deciles based on the implied volatility spread VS in the previous month. The mispricing-and-volatility-spread portfolio is limited to the bottom VS decile. It goes long on the stocks in the bottom MISP decile and short on the stocks in the top MISP decile. This portfolio is rebalanced at the end of each month. We construct both the equal-weighting and value-weighting portfolios in this manner. We further calculate the monthly returns to these portfolios and examine their monthly alphas using standard asset pricing models.

Table 7 reports the results the returns and alphas to the long legs and short legs of the compound strategy. We report both equal-weighting and value-weighting portfolios. As we can see immediately, among the bottom VS quintiles, the long legs (i.e., the low MISP) exhibit strongly positive returns around 1.21% (1.18%) for equal-weighting (value-weighting). In comparison, the most overpriced stocks (i.e., the high MISP) register returns of around -0.72% (-0.56%) for equal-weighting (value-weighting). Combining the two legs suggests that this strategy is highly profitable with an average return of 1.93% (1.73%) under equal (value) weighting.

For robustness check, we report the risk-adjusted returns using four alternative risk adjustment specifications. It is obvious we observe similar patterns for risk-adjusted returns across the four specifications. The compound strategy seems to be highly profitable. For instance, the alpha from the Fama-French-Carhart four-factor stands at 1.19% (1.23%) per month for the long leg and -0.86% (-0.87%) per month for the short leg under equal (value) weighting.

Interestingly, when we replicate the portfolio strategy using stocks that are in the top VS quintiles, we find that such a hedge portfolio is not profitable at all. While both the long legs still yield abnormal returns, the hedge portfolio barely generates any abnormal returns. This clearly suggests that professional money managers should focus on the low VS stocks when implementing the mispricing strategy.

5. Conclusions

In this paper, we examine the important issue of stock mispricing through the lens of the trading activities in the options market. We show that the implied volatility spread constructed from the options market has significant predictive power on subsequent stock mispricing. We believe this is consistent with the notion that informed trading helps incorporate new information into asset prices and reduce stock mispricing, thus making the stock price more informative.

We further show the stock mispricing mitigation effect is more pronounced when the options trading volume is much higher. We interpret this finding as evidence consistent with the notion that the heightened options trading provides better camouflage for informed traders, thus validating Kyle (1985) Admati and Pfleiderer (1988).

Our paper also provides new insights to the professional money management industry. We construct an investment strategy that exploits the stock mispricing conditioning on the implied volatility spread. We show that a self-financing monthly portfolio that goes long on most underpriced stocks and short on most overpriced stocks when the implied volatility spread is the lowest yields statistically and economically significant abnormal returns. We believe this is certainly intriguing to professional money managers.

Appendix: variable definitions

MISP: is a measure for stock mispricing. This measure is constructed by following the procedures outlined in Stambaugh et al. (2015). It is the simple average of the ranking percentile based on 11 asset pricing anomalies including net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment to assets, distress, O-score, momentum, gross profitability premium, and return on assets. *MISP* ranges between 0 and 100. Stocks with the highest values of *MISP* are the most overpriced and those with the lowest values are the most underpriced.

SUV: *SUV* is the standardized unexplained volume as a proxy for investors' divergence of opinions. To construct this measure, we follow the procedures outlined in Garfinkel (2009). Specifically, we estimate the standardized unexplained volume (*SUV*) using a methodology similar to the market approach to estimate market returns:

$$UV_{i,t} = Volume_{i,t} - E[Volume_{i,t}]$$

$$E[Volume_{i,t}] = \hat{\alpha}_i + \hat{\beta}_1 \cdot |R_{i,t}|^{+} + \hat{\beta}_2 \cdot |R_{i,t}|^{-}$$

$$SUV_{i,t} = \frac{UV_{i,t}}{S_{i,t}}$$

Note $S_{i,t}$ is the standard deviation of the residuals from the regression, calculated over the model's estimate period.

SIZE: *SIZE* is the firm size. Consistent with the existing literature, firm size is measured by the natural logarithm of the market value of equity (a stock's price times shares outstanding scaled by 10^6) at the end of month t-1 for each stock.

ILLIQ: *ILLIQ* is the firm-level illiquidity. Following Amihud (2002), we measure stock illiquidity for each stock in month t as the ratio of the absolute monthly stock return to its dollar trading volume (scaled by 10^7).

$$ILLIQ_{i,t} = |R_{i,t}| / VOLD_{i,t}$$

where $R_{i,t}$ is the return on stock i in month t, and $VOLD_{i,t}$ is the corresponding monthly trading volume in dollars.

IOR: *IOR* is the institutional ownership. Institutional ownership data are extracted from Thomson Reuters Institutional Holdings (S34) database. *IOR* is defined as the institutional ownership divided by the shares outstanding.

IVOL: is the idiosyncratic volatility. To estimate the monthly idiosyncratic volatility of an individual stock, we employ the Fama-French three-factor model to estimate the following equation:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i (R_{m,d} - r_{f,d}) + \gamma_i SMB_{m,d} + \eta_i HML_{m,d} + \varepsilon_{f,d}$$

The idiosyncratic volatility of stock i in month t is defined as the standard deviation of daily residuals in month t.

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Table 1: Summary statistics of main variables

This table presents the summary statistics of the main variables used in the empirical analysis. *MISP* is the stock mispricing measure following Stambaugh et al. (2015). *VS* is options implied volatility spread. *Size* is the natural log of the market capitalization. *Illiq* is Amihud's illiquidity measure scaled up by 10^6. *OptVol* is total monthly option trading volume including both calls and puts. *SUV* is the standardized unexplained volume following Garfinkel (2009). *IOR* is the institutional ownership. *IVOL* is the idiosyncratic volatility. The methodology to construct all variables is described in the Appendix. The table presents the mean, median, standard deviation, the 5th, the 25th, the 75th, and the 95th percentiles using the pooled sample of all firm months from January 1996 to December 2016.

Variable	No. of Obs.	Mean	Std. Dev.	5th	25th	Median	75th	95th
MISP	315629	49.350	12.904	29.190	40.100	48.710	57.970	71.800
VS	315629	-0.010	0.040	-0.050	-0.014	-0.005	0.000	0.014
Size	315629	21.355	1.515	19.176	20.248	21.188	22.267	24.121
Illiq	315629	0.006	0.038	0.000	0.000	0.001	0.004	0.023
OptVol	315628	19638.67	119765.59	0	87	838	6715	77156
SUV	315629	0.120	0.842	-0.695	-0.335	-0.034	0.385	1.355
IOR	315629	0.756	0.243	0.257	0.645	0.805	0.917	1.057
IVOL	315629	0.019	0.013	0.006	0.010	0.015	0.023	0.041

Table 2: Correlation Structure of the Main Variables

This table examines the correlation structure among the main variables used in the empirical analysis. The main variables include the stock mispricing *MISP*, option implied volatility spread *VS*, firm size *SIZE*, Amihud's Illiquidity *Illiq*, institutional ownership *IOR*, monthly option trading volume *OptVol*, standardized unexplained volume *SUV*, and idiosyncratic volatility *IVOL*. The table presents the correlation coefficients using the pooled sample. P-values are included in the parentheses.

	MISP	*VS*	*Size*	*Illiq*	*IOR*	*OptVol*	*SUV*	*IVOL*
MISP	1	-0.0583	-0.2647	0.0385	-0.0878	-0.0374	0.0120	0.2187
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
VS		1	0.0255	-0.0019	0.0893	-0.0089	0.0269	-0.0821
			(<.0001)	(0.2856)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Size			1	-0.1990	0.0762	0.2926	-0.0169	-0.3521
				(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Illiq				1	-0.1114	-0.0236	-0.0199	0.0755
					(<.0001)	(<.0001)	(<.0001)	(<.0001)
IOR					1	-0.0362	-0.0049	-0.0390
						(<.0001)	(0.0055)	(<.0001)
OptVol						1	0.0288	0.0131
							(<.0001)	(<.0001)
SUV							1	0.3214
								(<.0001)
IVOL								1

Table 3: Average Returns on portfolios of stocks sorted both by MISP and Implied Volatility Spread

Every month from January 1996 to December 2016, stocks are sorted into ten deciles based on the stock mispricing *MISP*. Within each decile, stocks are further sorted into ten deciles based on implied volatility spread *VS* in the previous month. The table presents the average returns of the 100 portfolios. Panel A (B) reports the average returns for the equal-weighted (value-weighted) portfolios.

Panel A: Equal Weighting										
	Low VS	2	3	4	5	6	7	8	9	High VS
Low MISP	0.0121	0.0105	0.0070	0.0088	0.0132	0.0097	0.0078	0.0112	0.0104	0.0100
2	0.0096	0.0102	0.0102	0.0116	0.0101	0.0134	0.0084	0.0121	0.0127	0.0103
3	0.0092	0.0120	0.0090	0.0098	0.0118	0.0115	0.0089	0.0090	0.0132	0.0157
4	0.0122	0.0102	0.0130	0.0116	0.0135	0.0111	0.0100	0.0125	0.0117	0.0095
5	0.0099	0.0103	0.0120	0.0088	0.0099	0.0112	0.0116	0.0142	0.0106	0.0121
6	0.0104	0.0100	0.0147	0.0108	0.0117	0.0123	0.0142	0.0136	0.0129	0.0165
7	0.0094	0.0090	0.0089	0.0134	0.0089	0.0128	0.0131	0.0113	0.0107	0.0163
8	0.0064	0.0115	0.0128	0.0130	0.0130	0.0092	0.0136	0.0098	0.0145	0.0121
9	0.0054	0.0046	0.0115	0.0117	0.0120	0.0077	0.0126	0.0113	0.0104	0.0109
High MISP	-0.0072	0.0010	0.0090	0.0095	0.0098	0.0109	0.0087	0.0103	0.0140	0.0093
Panel B: Value Weighting										
	Low VS	2	3	4	5	6	7	8	9	High VS
Low MISP	0.0118	0.0082	0.0042	0.0076	0.0135	0.0074	0.0097	0.0134	0.0078	0.0088
2	0.0123	0.0097	0.0074	0.0091	0.0053	0.0104	0.0074	0.0095	0.0118	0.0069
3	0.0090	0.0094	0.0057	0.0119	0.0120	0.0090	0.0072	0.0070	0.0097	0.0150
4	0.0132	0.0103	0.0114	0.0109	0.0121	0.0127	0.0109	0.0115	0.0137	0.0079
5	0.0091	0.0057	0.0072	0.0126	0.0099	0.0109	0.0102	0.0103	0.0060	0.0114
6	0.0069	0.0108	0.0147	0.0091	0.0116	0.0066	0.0109	0.0100	0.0087	0.0160
7	0.0072	0.0127	0.0072	0.0116	0.0078	0.0151	0.0085	0.0068	0.0109	0.0170
8	0.0054	0.0090	0.0131	0.0084	0.0087	0.0048	0.0139	0.0087	0.0199	0.0170
9	0.0100	0.0054	0.0090	0.0087	0.0089	0.0042	0.0076	0.0078	0.0089	0.0088
High MISP	-0.0056	0.0045	0.0039	0.0061	0.0095	0.0044	0.0084	0.0042	0.0162	0.0040

Table 4: Alphas on portfolios of stocks sorted both by MISP and Implied Volatility Spread

Every month from January 1996 to December 2016, stocks are sorted into ten deciles based on the stock mispricing MISP. Within each decile, stocks are further sorted into ten deciles based on implied volatility spread in the previous month. The table presents the four-factor Fama-French-Carhart alphas for the 100 portfolios. Panel A (B) reports the alphas for the equal-weighted (value-weighted) portfolios.

Panel A: Equal Weighting										
	Low VS	2	3	4	5	6	7	8	9	High VS
Low MISP	0.0119	0.0097	0.0064	0.0079	0.0127	0.0098	0.0077	0.0107	0.0097	0.0101
2	0.0088	0.0094	0.0098	0.0103	0.0093	0.0132	0.0077	0.0117	0.0116	0.0094
3	0.0091	0.0113	0.0083	0.0090	0.0105	0.0103	0.0081	0.0080	0.0117	0.0148
4	0.0107	0.0095	0.0120	0.0106	0.0125	0.0105	0.0093	0.0124	0.0106	0.0090
5	0.0084	0.0086	0.0107	0.0077	0.0089	0.0103	0.0105	0.0132	0.0097	0.0100
6	0.0090	0.0091	0.0130	0.0098	0.0106	0.0111	0.0128	0.0124	0.0117	0.0159
7	0.0072	0.0076	0.0077	0.0112	0.0078	0.0118	0.0117	0.0098	0.0094	0.0148
8	0.0047	0.0085	0.0113	0.0111	0.0112	0.0081	0.0115	0.0089	0.0132	0.0105
9	0.0028	0.0024	0.0104	0.0103	0.0109	0.0054	0.0106	0.0094	0.0083	0.0089
High MISP	-0.0086	-0.0017	0.0061	0.0067	0.0074	0.0091	0.0063	0.0085	0.0118	0.0063
Panel B: Value Weighting										
	Low VS	2	3	4	5	6	7	8	9	High VS
Low MISP	0.0123	0.0079	0.0034	0.0069	0.0124	0.0078	0.0091	0.0140	0.0078	0.0093
2	0.0126	0.0091	0.0070	0.0086	0.0051	0.0092	0.0066	0.0096	0.0121	0.0061
3	0.0098	0.0087	0.0052	0.0114	0.0112	0.0077	0.0065	0.0051	0.0081	0.0156
4	0.0126	0.0101	0.0106	0.0097	0.0114	0.0115	0.0107	0.0107	0.0133	0.0079
5	0.0089	0.0038	0.0058	0.0112	0.0086	0.0101	0.0086	0.0095	0.0041	0.0104
6	0.0063	0.0103	0.0127	0.0081	0.0108	0.0049	0.0100	0.0090	0.0078	0.0161
7	0.0050	0.0123	0.0059	0.0095	0.0064	0.0149	0.0070	0.0054	0.0094	0.0157
8	0.0043	0.0072	0.0127	0.0081	0.0065	0.0037	0.0121	0.0075	0.0186	0.0165
9	0.0076	0.0033	0.0071	0.0073	0.0076	0.0021	0.0054	0.0064	0.0070	0.0080
High MISP	-0.0087	0.0017	0.0031	0.0038	0.0075	0.0033	0.0066	0.0030	0.0143	0.0002

Table 5: Firm-level cross sectional regression using implied volatility spread

This table presents the Fama-MacBeth regression results of predicting the stock mispricing MISP using the option implied volatility spread VS. Each month from January 1996 to December 2016, nested versions of the following cross-sectional regression equation are estimated:

$$MISP_{i,t} = \beta_o + \beta_1 VS_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 SUV_{i,t-1} + \beta_4 Illiq_{i,t-1} + \beta_5 IVOL_{i,t-1} + \beta_6 IOR_{i,t-1} + \varepsilon_{i,t}$$

All variables are as defined in the Appendix. This table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics (in parentheses). ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	49.0866***	95.9923***	95.8814***	97.1811***	83.7539***	87.1883***
	(404.62)	(42.25)	(42.12)	(43.54)	(41.83)	(46.55)
VS	-25.4440***	-24.2142***	-24.2788***	-24.1555***	-20.9707***	-18.1830***
	(-9.84)	(-8.44)	(-8.50)	(-8.43)	(-6.66)	(-5.83)
Size		-2.1946***	-2.1909***	-2.2468***	-1.7736***	-1.7979***
		(-20.40)	(-20.33)	(-21.35)	(-19.27)	(-19.57)
SUV			-0.1307***	-0.1193***	-0.8525***	-0.8562***
			(-2.93)	(-2.71)	(-8.19)	(-8.19)
Illiq				-8.8962*	-13.5118***	-26.0483***
				(-1.91)	(-5.80)	(-5.80)
IVOL					182.3194***	179.9950***
					(10.99)	(10.68)
IOR						-3.6714***
						(-9.03)

Table 6: The role of option trading volume

This table presents the Fama-MacBeth regression results of predicting the stock mispricing MISP using the option implied volatility spread VS. Each month from January 1996 to December 2016, nested versions of the following cross-sectional regression equation are estimated:

$$MISP_{i,t} = \beta_o + \beta_1 VS_{i,t-1} + \beta_2 OptVol_{i,t-1} + \beta_3 VS \cdot OptVolze_{i,t-1} + \beta_4 Size_{i,t-1} + \beta_5 SUV_{i,t-1} + \beta_6 Illiq_{i,t-1} + \beta_7 IVOL_{i,t-1} + \beta_8 IOR_{i,t-1} + \varepsilon_{i,t}$$

All variables are as defined in the Appendix. This table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics (in parentheses). ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	51.6243***	104.1865***	104.1582***	104.4206***	87.0161***	91.9168***
	(346.13)	(38.00)	(37.73)	(38.43)	(36.10)	(40.24)
VS	-1.6414	-6.1840*	-6.4115*	-6.3310*	-7.7807**	-5.578
	(-0.42)	(-1.71)	(-1.76)	(-1.80)	(-2.22)	(-1.64)
OptVol	0.3983***	0.4519***	0.4534***	0.4517***	0.1542***	0.1943***
	(12.77)	(12.20)	(12.08)	(11.95)	(4.85)	(6.12)
*VS*OptVol*	-5.4517***	-2.4201***	-2.3896***	-2.3831***	-1.8169***	-1.7699***
	(-8.70)	(-4.45)	(-4.38)	(-4.53)	(-3.64)	(-3.62)
Size		-2.7148***	-2.7146***	-2.7257***	-1.9548***	-2.0472***
		(-19.82)	(-19.67)	(-20.09)	(-17.10)	(-18.00)
SUV			-0.0348	-0.0351	-0.7853***	-0.7825***
			(-0.81)	(-0.82)	(-7.32)	(-7.29)
Illiq				0.4488	-7.3439	-20.8891***
				(0.09)	(-1.43)	(-4.26)
IVOL					158.3267***	152.2433***
					(8.59)	(8.13)
IOR						-3.9610***
						(-9.90)

Table 7: Returns and alphas of the portfolios formed by the stock price mispricing and the implied volatility spread

Every month from January 1996 to December 2016, stocks are sorted into ten deciles based on the stock mispricing MISP. Within each MISP decile, stocks are further sorted into ten deciles based on option implied volatility spread VS over the previous month. Within the top and bottom VS deciles, a self-financing portfolio goes long on the stocks in the bottom MISP decile and short on the stocks in the top MISP decile. The table reports the equal-weighted (EW) and value-weighted (VW) portfolio average monthly returns, the standard deviation, and the abnormal returns from the CAPM, Fama-French three-factor model, the Fama-French-Carhart four-factor model, the Fama-French four-factor model augmented with the Pastor and Stambaugh liquidity factor. Panel A and B report equal weighting and value weighting, respectively. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Panel A: Equal Weighting						
	Low VS			High VS		
	Low MISP	High MISP	Low MISP – High MISP	Low MISP	High MISP	Low MISP – High MISP
Average return	0.0121	-0.0072	0.0193	0.0100	0.0093	0.0006
std dev	0.0485	0.0820	0.0557	0.0537	0.0881	0.0571
CAPM Alpha	0.0116***	-0.0091	0.0207***	0.0095**	0.0054	0.0041
	(2.83)	(-1.41)	(5.86)	(2.21)	(0.87)	(1.05)
FF Alpha	0.0119***	-0.0089	0.0208***	0.0098**	0.0057	0.0041
	(2.93)	(-1.40)	(5.81)	(2.33)	(0.92)	(1.06)
FFC Alpha	0.0119***	-0.0086	0.0205***	0.0101**	0.0063	0.0038
	(2.95)	(-1.35)	(5.71)	(2.39)	(1.04)	(1.03)
FFCPS Alpha	0.0118***	-0.0082	0.0200***	0.0102**	0.0059	0.0042
	(2.88)	(-1.21)	(5.11)	(2.32)	(0.98)	(1.14)
Panel B: Value Weighting						
	Low VS			High VS		
	Low MISP	High MISP	Low MISP – High MISP	Low MISP	High MISP	Low MISP – High MISP
Average return	0.0118	-0.0056	0.0173	0.0088	0.0040	0.0048
std dev	0.0421	0.0791	0.0676	0.0510	0.0948	0.0746
CAPM Alpha	0.0122***	-0.0092	0.0214***	0.0082**	0.0010	0.0072
	(3.20)	(-1.38)	(4.65)	(2.16)	(0.13)	(1.21)
FF Alpha	0.0123***	-0.0090	0.0214***	0.0083**	0.0014	0.0069
	(3.34)	(-1.39)	(4.67)	(2.26)	(0.19)	(1.24)
FFC Alpha	0.0123***	-0.0087	0.0211***	0.0087**	0.0020	0.0067
	(3.31)	(-1.35)	(4.58)	(2.34)	(0.26)	(1.17)
FFCPS Alpha	0.0121***	-0.0086	0.0207***	0.0087**	0.0015	0.0072
	(3.22)	(-1.28)	(4.19)	(2.30)	(0.19)	(1.23)