Idiosyncratic Volatility and Stock Returns: Does Option Trading Reduce Stock Market Mispricing?

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Abstract

Theory suggests that options may play an important role in improving information efficiency of financial markets. This study empirically examines whether option trading reduces stock market mispricing in the form of the idiosyncratic volatility (IVOL) anomaly, i.e., the negative relation between idiosyncratic volatility and future stock returns. We find that the IVOL anomaly is intensified rather than reduced among stocks with active option trading, and that options of these stocks exhibit a similar magnitude of mispricing. We further document that the magnitude of the IVOL anomaly is positively correlated with two measures of relative option trading activity – the ratio of option trading volume to stock trading volume and the ratio of option open interest to stock trading volume. In addition, there is a stronger negative relation between IVOL and future earnings surprises among stocks with higher relative option trading activities. These findings are consistent with a hypothesis that some option traders have private information about future stock returns, and that such private information is first revealed in option trading activity before being incorporated into option prices or stock prices.

JEL Classification: G10; G12; G13.

Keywords: Idiosyncratic volatility; equity option.

I. Introduction

Ang, Hodrick, Xing, and Zhang (2006; 2009) report that stocks with higher idiosyncratic return volatility subsequently experience lower returns, in the US and in international stock markets. Their finding runs contrary to the prediction of standard asset pricing models, and is a surprise from the perspective of alternative models in which idiosyncratic risk does matter – for example, models based on under-diversification (Merton 1987) or based on the effect of narrow framing (Barberis and Huang 2001) suggest a positive relation between idiosyncratic risk and expected return. This idiosyncratic risk anomaly has since attracted considerable attention among researchers, including a few studies that contemplate on its possible causes. The proposed explanations range from investor under-reaction to information about firms' future operating performance (Jiang, Xu, and Yao 2009), the combined effect of short-sale constraint and difference of opinion (Boehme, Danielsen, Kumar, and Sorescu 2009), to the pursuit of idiosyncratic skewness by marginal investors in high IVOL stocks (Boyer, Mitton, and Vorkink 2009).

In this study, we investigate whether active option trading mitigates the mispricing associated with idiosyncratic volatility. Our study is motivated by the theoretical role options play in improving the information efficiency of financial markets. First pointed out by Black (1975) and subsequently illustrated in many studies (e.g., Back 1992; Bias and Hillion 1994; Easley, O'Hara, and Srinivas 1998), investors with private information may prefer to trade in the option market rather than in the stock market because options offer higher leverages. There are at least two mechanisms through which informed trading in the option market may cause underlying stocks to be priced efficiently. First, if option investors have private information, investors in the stock market may be able to infer such private information from observed option prices and option trading activities. Grossman (1997) provides a theoretical model in which derivative prices contain non-redundant valuation information and improve information aggregation by investors. Cao (1999) further shows that the introduction of derivative assets has the dual effects of encouraging private information production and improving price efficiency. The second mechanism is that options enable investors to overcome frictions in the underlying stock market such as the short-sale constraint. Thus, if investors have unfavorable information about a stock but cannot short-sell in the stock market, they can instead trade on options, which in turn may facilitate the incorporation of negative information into stock prices (e.g., Diamond and Verrecchia 1987; Figlewski and Webb 1993).

The idiosyncratic volatility anomaly makes a prime candidate for studying the effect of option trading on stock mispricing. According to Ang, et al. (2006), the mispricing associated with idiosyncratic volatility (IVOL) is mainly in the form of particularly low returns to the high-IVOL stocks; on the other hand, stocks with low or medium IVOL do not appear to have abnormal returns. Thus, to take advantage of this anomaly, the ability to short-sell high IVOL stocks is critical. Indeed, some researchers have conjectured (e.g., Boehme, et al. 2009) that short-sale constraints are the origin of this anomaly. Further, Jiang et al. (2009) document a strong negative relation between IVOL and firms' future earnings; they point out that marginal investors may have under-reacted to earnings-related information contained in IVOL. If this is the case, informed option traders need not to directly trade on IVOL for their trading to affect the magnitude of this anomaly – if they have private information about firms' future earnings and trade on it, the two mechanisms described above can help impound such information into stock prices and thus reduce IVOL-related mispricing.

Our study is also related to, and motivated by, the following three strands of the empirical literature. First, a few studies have investigated the issue of whether option traders have private information. For example, Easley, O'Hara, and Srinivas (1998) and Pan and Poteshman (2006) find that option trading volume signed by trading direction and option trades initiated by option buyers have power to predict underlying stock returns. Lee and Amin (1997), Cao, Chen, and Griffin (2005), and recently Roll, Schwartz, and Subrahmanyan (2009) find evidence of informed option trading prior to earnings announcements and corporate takeovers. However, these studies do not provide direct evidence on whether informed trading in the option market translates into improved efficiency in option prices and stock prices.

On the other hand, a strand of studies attempts to address the efficiency question by focusing on whether option prices lead stock prices in the price discovery process. The results from these studies are mixed. While some studies report evidence that option prices lead stock prices (e.g., e.g., Manaster and Rendleman, 1982; Bhattacharya 1987; Diltz and Kim 1996), others either do not find such evidence or find the opposite (e.g., Vijh 1988, Stephan and Whaley, 1990; Chan, Chung, and Johnson 1993; O'Connor 1999). Our paper, by analyzing option trading in the context of a market anomaly, introduces a novel way to assess the informational role of options.

There is also an empirical debate on whether options are effective instruments to overcome short-sale constraints in the stock market. Based on daily closing prices of options and stocks, Ofek, Richardson, and Whitelaw (2006) report frequent violations of the put-call parity, and link such violations to the short-sale constraints in the stock market. Lamont and Thaler (2003) also report substantial violations of the put-call parity when analyzing the relative mispricing between carve-outs and parent firms. The findings in these studies suggest that the relative mispricing between options and underlying stocks is difficult to arbitrage away when short-sale is difficult, and as a consequence, option traders' information may not always be effectively passed to the stock prices. However, using intraday pricing data that better match the time stamps of option and stock quotes, Battalio and Schultz (2006) find that violations of the put-call parity are infrequent for internet stocks during the NASDAQ bubble period. They conclude that it is not difficult to synthetically short internet stocks using options, and point out that investors do not substantially engage in such synthetic short-selling because mispricing of internet stocks "was not as obvious then as it is now with the benefit of hindsight."Our study puts the effectiveness of options to overcome short-sale constraints under a new test where hindsight of mispricing is not an issue. This is because, as mentioned earlier, informed investors need not to be directly trading on IVOL; their private information about firms' future earnings may lead them to trade in the same direction as the IVOL anomaly suggests.

The impact of option trading on a stock market anomaly depends on whether option traders have private information about stock returns, and how effectively they trade on such information. Consequently there are three possible outcomes. The strongest outcome, ranked in terms of the efficiency of option and stock prices, is that aggressive trading by informed option investors completely eliminates the stock return anomaly. In this case both the stock price and option price have no mispricing for the subset of stocks with active trading, but mispricing may continue to exist for other stocks. In a semi-strong outcome, informed option trading causes options to be efficiently priced, but the underlying stock prices remain mispriced. This may involve some form of violation of no-arbitrage conditions, due to frictions (e.g., Lamont and Thaler 2003; Ofek, Richardson, and Whitelaw 2006). Finally, in a weak outcome, option trading fails to correct mispricing in either the option market or the stock market. That is, both options and stocks are mispriced. This may occur when option traders have no private information, or when option traders execute their trades very effectively to hide their private information.

Our basic empirical finding is that, perhaps surprisingly, the weak outcome prevails. Based on the OptionMetrics Ivy DB data for the period from 1996 to 2008, in each month we select a subsample of common stocks with active option trading. For this sample we can measure the underlying stock returns as well as returns to option-based synthetic stock positions that approximately replicate the underlying stock prices.[1] We find that the IVOL anomaly is stronger within this subsample of stocks than in the entire stock sample. Specifically, for equal-weighted stock decile portfolios sorted on IVOL within the entire stock sample, the bottom IVOL stock decile outperforms the top decile by 1.23% during the next month. By contrast, when we only keep stocks with active option trading in each IVOL decile, the resulting bottom-top decile return spread increases to 1.74% per month. The larger bottom-top return spread for the option trading subsample is mainly due to lower returns to the top IVOL decile stocks: -0.27% in the entire stock sample, versus -0.78% in the option trading subsample. Option-based synthetic stock returns exhibit the same pattern across IVOL deciles: the bottom-top decile difference

[1]Specifically, a synthetic stock position involves buying a call, selling a put with the same maturity and strike price, and holding risk-free assets amounting to the present value of strike price and expected dividends. A main reason for us to choose this synthetic stock approach, rather than looking at calls or puts separately, is that the synthetic stock returns should closely track underlying stock returns if the put-call parity holds (except for an early exercise premium). This offers an advantage when it comes to the estimation of abnormal returns, or alphas: if a linear factor model is valid for stock returns when estimating alphas, it should also to a large extent be valid for the synthetic stock returns. On the other hand, returns to straight calls and puts are subject to factors other than underlying stock returns, such as maturity and volatility. Measuring their abnormal returns is more challenging. In addition, calls and puts may exhibit other patterns of mispricing, such as those documented by Bakshi and Kapadia (2003), Coval and Shumway (2003), Goyal and Saretto (2009), Doran and Fodor (2008), and Cao and Han (2009), thus confounding the inference on IVOL-related mispricing. Synthetic stock returns are much less subject to such confounding effects.

in synthetic stock return is 1.68% per month, and the synthetic return to the top decile is particularly low, at -0.73%. That is, options are similarly mispriced.

These results indicate that active option trading does not mitigate the idiosyncratic volatility anomaly, but rather intensifies mispricing on underlying stocks and instigate similar mispricing on options. Thus, if option traders indeed have private information about stock returns, they must have executed their trades effectively to hide their private information. This is consistent with the idea proposed by Easley et al. (1998), that option trading activity reveals the existence of private information before such information is impounded into option prices or stock prices. We further hypothesize that the intriguing outcome of option trading exacerbating the anomaly is due to a selection effect by informed option trading. While on average high IVOL stocks have low future returns, there may be some high IVOL stocks with bad news, for example, with truly disappointing future earnings, whereas other high IVOL stocks do not. If some traders have private information about which high IVOL stocks are really going to report poor earnings, their option trades are likely to be concentrated on such stocks. Therefore, among high IVOL stocks, those with active option trading are more likely to have negative news to come, hence lower future returns. In other words, option trading is a signal of the intensity of private information.

To examine this hypothesis, we take advantage of an empirical measure of informed option trading activity recently developed by Roll, Schwartz, and Subrahmanyan (2009). Their measure O/S is the ratio of trading volume for all options on an underlying stock to the trading volume of the stock.[2] In each month we sort all stocks with any option listing into three groups based on O/S. Within the low O/S group, stocks in the bottom IVOL decile outperform those in the top decile by 0.71% per month. By contrast, in the high O/S group, stocks in the bottom IVOL decile outperform those in the top decile by 1.89%. This result is consistent with the selection

[2] Several existing studies, such as Easley et al. (1998) and Pan and Poteshman (2006), have developed measures of informed option trading activity using transaction level option data. However, their data are proprietary. We therefore resort to the relative option trading activity measure O/S, which can be constructed using the OptionMetrics data. On an ex ante basis, O/S can be a proxy for either informed trading or dispersion of option traders' opinions (Choy and Wei 2009). The same point can be made for our second measure, option open interest relative to stock volume (OI/S). However, Roll et al. (2009) find that O/S is positively related to the magnitude of stock returns around subsequent earnings announcement. Amin and Lee (1997) find that open interest is positively related the magnitude of subsequent earnings announcement returns. Such evidence lends support to the use of O/S and OI/S as empirical measures of information option trading.

effect of informed option trading. Since option traders are likely to purchase call options if they have positive information and purchase put options if they have negative information, we further define call O/S and put O/S measures, using trading volume on calls and puts separately. We find that among high IVOL stocks, those with high put O/S have much lower returns than those with low put O/S. On the other hand, among low IVOL stocks there is no significant return difference between low call O/S and high O/S groups. This suggests that option traders' private information is concentrated on high IVOL stocks.

The results are even stronger when the analysis is repeated using an alternative measure of informed option trading, OI/S, which is the ratio of open interest of all options for an underlying stock to the stock trading volume. To highlight, in the low OI/S group, stocks in the bottom IVOL decile outperform those in the top IVOL decile by 0.64% per month. By contrast, in the high OI/S group, stocks in the low IVOL decile outperform those in the high IVOL decile by 2.11%.

It is documented that the relation between idiosyncratic volatility and future earnings surprises is a plausible cause of the IVOL anomaly (e.g., Jiang et al. 2009). Given this result, we hypothesize that option traders' private information is in the form of soon-to-be-announced corporate earnings. To verify, we compare quarterly earnings that are reported within the three months after portfolio formation, across firms with different IVOL and different relative option trading activity measures. We find that stocks with higher IVOL have substantially lower return on equity (ROE) and standardized unexpected earnings (SUE). Moreover, among high IVOL stocks, those with higher OS or OI/S have significantly lower ROE and SUE. This is further evidence that relative option trading activity reveals option traders' private information.

It is important to note that, while the findings are consistent with the existence of private information in the option market, they also suggest that information transmission from the option market to the stock market is not effective. Unlike the measure of informed option trading introduced by Pan and Poteshman (2006) that is based on non-public data, option trading activity measures O/S and OI/S are easily observed by both option and stock market investors. Yet marginal investors fail to take advantage of such public information when they value options and stocks.

Finally, we perform analysis to assess whether options can be effectively used to overcome short-sale constraints in the stock market. Specifically, assuming that it may be difficult to short high IVOL stocks directly, we explore the profitability of trading on the IVOL anomaly using option-based synthetic stock positions. The main obstacle for this strategy is option trading cost. Historically, option trading costs are high (e.g., Vijh 1990); in recent years, they have come down substantially due to competition (e.g., Mayhew 2002). We find that during our sample period option bid-ask spreads are high on average, and particularly high for high IVOL stocks. Even under the assumption that effective spreads are only 50% of quoted spreads, option trading costs easily outsize any paper gains from the synthetic stock strategies.

To sum, we take a novel approach to analyze the information role of options, in the context of a well-known stock market anomaly. Our findings are consistent with the existence of private information possessed by some option traders, and such information is concentrated on a subset of stocks with high idiosyncratic volatility. However, active option trading does not mitigate mispricing. Rather, the anomaly is stronger among stocks with active option trading and option prices exhibit similarly strong mispricing. This suggests that mechanisms for option trading to improve stock price efficiency are not effective, at least in the context of the anomaly we examine.

The rest of the paper is organized as follows. Section II describes the option and stock data sample, the measure of idiosyncratic volatility, and synthetic stock positions. Section III provides empirical results. Section IV concludes.

II. Data and Methodology

II.A. Stock Sample and Idiosyncratic Volatility Measure

The stock data are from CRSP. For the period from January 1996 to September 2008 (during which we have options data), in each month we select all common stocks with valid IVOL estimates (defined below) and with month-end price no less than $5. This constitutes our "entire stock sample". The exclusion of stocks with price below $5 is to alleviate market microstructure noise in measuring returns.

In each month, we estimate idiosyncratic volatility for each individual stock, IVOL, as the standard deviation of the estimated residuals from regressing daily stock returns (R_{it}) onto contemporaneous daily market returns (R_{mt}) as well as three lagged market returns:

$$R_{it} = a + b_0 R_{mt} + b_1 R_{mt-1} + b_2 R_{mt-2} + b_3 R_{mt-3} + e_{it} \tag{1}$$

The proxy for market return is the CRSP value-weighted index return. We require a minimum of 15 daily observations in a month for the IVOL estimate to be valid. We have also followed Ang et al. (2006) to estimate IVOL by including daily HML and SMB factors as additional explanatory variables. The results are similar to those based on equation (1).

Table I reports summary statistics on IVOL for the stock sample, for the whole sample period and for the three subperiods: 1996-2000, 2001-2004, and 2005-2008. Note that average IVOL is high during the first subperiod, but declines in the following two subperiods. This time trend has been reported in a few recent studies, e.g., Brandt, Brav, Graham, and Kumar (2008) and Bekeart, Hodrick, and Zhang (2009).

II.B. Option Data and Synthetic Stock Positions

The option data are from OptionMetrics Ivy DB. The dataset provides information on all U.S. exchange-traded options for individual stocks and includes daily closing quotes, strike price, expiration date, implied volatility (IMPVOL) estimates, open interest, volume, etc., from January 1996 through September 2008.

To analyze whether option prices are mispriced with respect to idiosyncratic volatility, we need a method to assess abnormal returns to options or option portfolios. Our approach is based on synthetic stock positions. To illustrate the idea, consider the the put-call parity, which holds for European options:

$$S = C - P + PV(D) + Xe^{-r\tau} \tag{2}$$

where S is the stock price, C and P are prices of a call and a put with the same strike price and same maturity, PV(D) is the present value of future dividends with ex-dividend dates prior to option expiration, X is the strike price, r is the riskfree rate for the maturity of the option, and τ is time to expiration. From this intuition we can create a synthetic stock position for a stock, by buying a call (C), writing a put (P) with same underlying stocks, maturity, and strike price, and holding a riskfree asset amounting to $PV(D) + Xe^{-r\tau}$. For European options, the put-call parity ensures that the return to this synthetic stock position should be the same as that to the underlying stock. For American options, the put-call parity described in equation (2) does not hold exactly, and an adjustment for the early exercise premium is required. Therefore, synthetic stock returns approximately track underlying stock returns. Our analysis, described later, suggests that differences between synthetic stock returns and underlying stock returns caused by early exercise premium are on average quite small for the options we examine.

There are three empirical advantages to the use of synthetic stock returns in evaluating magnitude of option mispricing with respect to IVOL. First, despite the complication brought by early exercise premium, the synthetic stock positions themselves are investable portfolios, whose returns are readily observable. Second, due to the proximity between synthetic returns and underlying stock returns, if an asset pricing model (e.g., CAPM, the Fama-French three-factor model, or the Carhart four-factor model) is valid for measuring mispricing on underlying stocks, it should be also largely valid for measuring mispricing on the synthetic stock positions. By contrast, individual options have time-varying risk and expected return due to changes in underlying stock prices, maturity, volatility, etc.. Therefore, the use of synthetic stocks largely avoids a complication when evaluating abnormal returns to options or option portfolios in general. Finally, individual stock options are subject to a few additional pricing irregularities. For example, volatility-sensitive option spread portfolios and delta-hedged option positions exhibit abnormal returns with respect to standard asset pricing models; see e.g., Bakshi and Kapadia (2003), Coval and Shumway (2003), Goyal and Saretto (2009), Doran and Fodor (2008), and Cao and Han (2009). Due to the put-call parity, returns to the synthetic stock positions are not subject to these confounding effects.

To ensure that the synthetic stock positions are investable portfolios and their returns can be measured using observed option quotes, we implement the following procedures to select a subsample of options from the OptionMetrics sample. We define an option pair as a call and a put on the same underlying stock, with the same strike price and maturity. In each month t, we select all such option pairs from OptionMetrics, and apply the following filters to select option pairs that are liquid and are feasible to buy and hold during the month of t+1. First, we only keep the option pairs that expire in month t+2.[3] This is to ensure the feasibility to hold these options during month t+1, as well as to have a desirable degree of liquidity that is typically associated with options at such short maturity. Second, we exclude an option pair if either the call or the put has no trading volume or no open interest, or has invalid implied volatility or invalid bid or offer quotes on the last trading day of the month. Invalid quotes are defined as either one side of the quotes being non-positive, or the offer being below the bid. Finally, within remaining option pairs, we select, for each underlying stock, the pair with strike price closest to the money (such options typically have high liquidity), and with moneyness between 0.5 and 1.5.[4] The resulting subsample of underlying stocks is referred to as the "option trading subsample".

We use the selected option pairs to construct synthetic stocks for the option sample, and hold these positions during the month of t+1. Values of these positions at the beginning and ending of a holding period are computed using the mid-quote prices of options (i.e., the average of offer and bid quotes). A difficulty in implementing this method is that while the option quotes are available for the beginning of the holding period by construction, they may not be available on the last trading day of month t+1. We get around this problem by using the valid quotes (positive offers and bids) from a trading day that is closest to, and within 3 trading days of, the last trading day of month t+1. Such a substitute date can be either in the end of month t+1 or in the beginning of month t+2. For robustness, we additionally examine synthetic stock returns by holding the positions until option expiration during month t+2.

Finally, the options that we use are of the American type. For the option put-call parity to

[3] All options on individual stocks expire on the Saturday after the third Friday of the expiration month.

[4] We do not impose tighter moneyness restriction, because informed investors may prefer trading on out-of-money options; see, e.g., Easley, et al. (1998).

hold, we should adjust American options' early exercise premium (EEP hereafter). The modified parity relation between stock price and American option prices is:

$$S = C - P + PV(D) + Xe^{-r\tau} + EEP_C - EEP_P \tag{3}$$

where EEPC and EEPP are early exercise premiums for the call and put respectively.

As a result, returns to our synthetic stock positions deviate from underlying stock returns. We account for such deviations when comparing these two sets of returns. In the appendix we provide details for EEP estimation.

III. Empirical Results

III.A. Returns to IVOL-sorted Portfolios

III.A.1. The Entire Stock Sample and The Option Trading Subsample

We first confirm that the idiosyncratic volatility anomaly exists in our entire stock sample, which, as defined earlier, consists of all common stocks with valid IVOL estimates and stock price no less than $5 at the end of a portfolio formation month.[5] From January 1996 to September 2008, in each month we form equal-weighted decile portfolios based on IVOL in the entire stock sample. When calculating portfolio returns, we include the delisting returns of individual stocks in the portfolios. Following Shumway (1998), when the CRSP delisting return is missing, we replace it with -30% if delisting is performance-related, and zero otherwise.

Table II reports average monthly returns to the decile portfolios and their Carhart (1997) four-factor alphas. We estimate the Carhart alphas by regressing the stock portfolio returns on the four factors – monthly CRSP value-weighted index return, the Fama-French size, book-to-market, and momentum factors. The factors are obtained from Ken French's website. The

[5] Bali and Cakici (2008) report that the IVOL anomaly does not exist based on equal-weighted portfolios, and Huang et al. (2009) find that in cross-sectional regressions, idiosyncratic volatility does not have power to predict future stock return once past stock return is controlled for. Jiang, Xu, and Yao (2009b) find that these results are driven by the inclusion of penny stocks and non-common stocks.

average number of stocks in each decile is approximately 435.

The results confirm the inverse relation between IVOL and future stock returns. Stocks in the lowest IVOL decile (D1) significantly outperform those in the highest IVOL decile (D10) by 1.23% per month. The t-statistic is significant at the 10% level. The return difference is mainly between the highest two deciles (D9 and D10) and the other eight deciles (D1 to D8). Returns exhibit only a slight downward trend from the first decile (D1) to the eighth decile (D8), but drop off sharply for the ninth (D9) and 10th (D10) deciles. A similar pattern is noted in the previous studies, e.g., Ang et al. (2006) and Jiang, et al. (2009).

The portfolio alphas exhibit a similar pattern. The alpha for the bottom-top difference in decile portfolio returns is 1.16%, with a t-statistic of 4.40. Alphas exhibit a slight downward drift from D1 to D8, and drop sharply for D9 and D10.

Under the perception that option trading improves information efficient of financial markets, the idiosyncratic volatility anomaly should be substantially weakened among stocks with actively traded options. We therefore examine the relation between IVOL and future returns for stocks within the "option trading subsample", which, as defined earlier, are those with at least a put-call pair that has positive trading volume, positive open interest, and valid quotes on the last trading day of the portfolio formation month.

We retain each stock's IVOL decile ranking formed within the entire stock sample, but when forming portfolios in each decile, only keep stocks within the option trading subsample. The average returns to the resulting equal-weighted decile portfolios are also reported in Table II. The number of stocks in each decile ranges from 28 to 37, substantially smaller than that for the portfolios based on the entire stock sample. The return to the bottom IVOL decile is 0.96%, same as the return to the bottom decile of the entire stock sample. However, the return to the top decile is -0.78%, substantially lower than the return to the top decile of the entire stock sample. As a consequence, the bottom-top return difference is also much higher, at 1.74%, with a t-statistic of 2.08. In addition, the returns are not much different from D1 to D8, but fall sharply in D9 and D10. This pattern is quite similar to that for the entire stock sample.

The patterns for the Carhart alphas are similar. From D1 to D8 there is a slight and nonmonotonic decline in alphas, while alphas for D10 are substantially lower. Also, D1 alphas are slightly lower for the option trading subsample relative to the entire stock sample. But there is a large difference in D10 alphas: -1.24% for the option trading subsample vs. -0.83% for the entire stock sample.

In untabulated analysis, we also examine the IVOL-return relation in three subperiods: 1996-2000, 2001-2004, and 2005-2008. In the entire stock sample, the mean (standard deviation) of the monthly D1-D10 return spreads are 1.13% (11.68%), 1.22% (8.41%), and 0.81% (3.26%). Note that the D1-D10 decile return in the third subperiod is lower than the first two periods. However, the return standard deviation of third subperiod is also substantially lower. In this sense, there is no significant mitigation of the IVOL anomaly over time. For the option trading subsample, the return pattern is similar albeit at a higher magnitude. The mean (standard deviation) of the monthly D1-D10 return spreads are 1.99% (13.50%), 2.24% (9.29%), and 0.84% (3.72%).

Overall, the results suggest that active option trading does not alleviate the IVOL anomaly. Rather, the anomaly is intensified among stocks with actively traded options, and the stronger mispricing is mainly due to even lower returns to the stocks in the highest IVOL decile.

III.A.2. Synthetic Stock Returns

We now turn to the question of whether options are also mispriced. In this part of analysis, we replace underlying stock returns in each decile portfolio by the respective synthetic stock returns described in Section II.B. For example, if month t+1 return of a stock in Decile K is 1% and its synthetic stock return during the same period is 1.2%, we replace 1% with 1.2% to compute Decile K returns for month t+1. Since the early exercise premium is not accounted for when we construct the synthetic positions, the returns to the synthetic positions will approximately, not perfectly, track the underlying stock returns even when the put-call parity always holds. Nonetheless, the synthetic stock positions are investable portfolios and the resulting synthetic returns are actual returns to these investable portfolios.

The resulting synthetic portfolio returns are reported in Table III. It turns out that synthetic portfolio returns are very close to the real portfolio returns reported in Table II. For example, D1 synthetic return is 0.95%, vs. D10 synthetic return of -0.73%. The bottom-top synthetic return difference is 1.68%, with a t-statistic of 2.05. The patterns on four-factor alphas for synthetic returns are also similar to those for actual returns. D1 synthetic alpha is 0.14%, and D10 synthetic alpha is -1.18%, resulting in a bottom-top difference in synthetic alpha of 1.32% (t=2.91). The results suggest that option prices are similarly mispriced, at about the same magnitude as that for underlying stocks.

The synthetic stock positions are investable portfolios and the synthetic stock returns can actually be obtained (before trading cost) by taking the synthetic stock positions. However, due to early exercise premium, synthetic stock prices differ from the actual stock prices. We further check if the abnormal synthetic stock returns are robust to the adjustment of early exercise premium. Specifically, in each month for each synthetic stock position we adjust both the beginning and ending synthetic stock prices during the portfolio holding month by EEP following Equation (3). Details for computing EEP for each option are provided in the appendix. We then compute EEP-adjusted synthetic stock returns using the EEP-adjusted synthetic stock prices.

The EEP-adjusted synthetic returns to IVOL decile portfolios are also reported in Table III. The result suggests that the effect of early exercise premium on synthetic stock returns across the IVOL deciles is quite small. For example, EEP-adjusted D1 synthetic return is 0.98%, and EEP-adjusted D10 synthetic return is -0.72%. The difference is 1.70%. These numbers are close to those without EEP adjustments. In addition, the table shows that the EEP-adjustment has a very small impact on the Carhart alphas for the synthetic portfolio returns.

The impact of EEP on option price depends on moneyness, time to maturity, as well as volatility. Most of the option pairs used in the synthetic stock positions are close to money, with relatively small magnitude of EEP. More importantly, it is the change of EEP during the portfolio holding month, not the level of EEP, that affects the returns computed above. This intuitively explains why EEP adjustment does not substantially influence our results at all.

Combining evidence from Table II and III, we find that rather surprisingly, the weak outcome prevails – option trading fails to mitigate mispricing in either the stock or the option market.

More intriguingly, the IVOL anomaly appears to be intensified among stocks with active option trading activity.

III.A.3. Portfolios Held Until Option Expiration

As mentioned earlier, on the last trading day of the portfolio holding month, not all options in our synthetic stock positions always have valid quotes. This creates a technical issue in computing synthetic returns. To deal with this, we use valid quotes on a trading day that is closest to the last trading day, as long as the substitute day is within three trading days before/after the last trading day of the month. A small number of options have to be excluded because they do not even have valid quotes within this window.

In this part of analysis, we check if our results are sensitive to our treatment of the end-of-month option quotes. Instead of holding the synthetic stock positions until the end of the month t+1, we extend the holding period until option expiration. By construction, all the option pairs used for synthetic stock positions expire on the Saturday after the third Friday of month t+2. Therefore, we hold the synthetic positions until this expiration date. The value of the long position in the call combined with the short position in the put is simply the underlying stock price minus the strike price.[6] Therefore, the calculation of holding-until-expiration synthetic returns does not involve option quotes at the end of this holding period.

We compute average returns and average synthetic stock returns to the holding-until-expiration portfolios (equal-weighted) and report the results in Table IV. The synthetic returns are not EEP adjusted. The stock return and synthetic return to the D1 decile are 1.73% and 1.72% respectively. The corresponding numbers for the D10 decile are -0.62% and -0.38%. The bottom-top differences are 2.35% and 2.10%, both significantly positive. Therefore, our conclusion on option mispricing is not sensitive to the assumption on option prices at the end of a holding period.

[6]Since options expire on the non-trading Saturdays, we use the closing stock price on the Fridays immediately prior to the expiration Saturdays to determine the payoffs to the synthetic stock positions.

III.A.4. Stocks with Option Listings vs. Stocks without Option Listings

Here we present an alternative way to gauge the influence of option trading on the IVOL anomaly. We classify all stocks in the entire sample into two groups: those with at least one option listed for trading and those without any option listing at the end of a portfolio formation month.

In Table V, we report returns to the IVOL deciles, separately for stocks without option listing and for stocks with option listing but keeping the IVOL decile rank obtained for the entire stock sample. For stocks without any option listing, the number of stocks in each IVOL decile ranges from 222 to 276. Portfolio returns reported here are based on actual individual stock return instead of synthetic return since the latter is no long all available for this group of stocks. The equal-weighted bottom decile portfolio (D1) return is 1.06% while that of the top decile (D10) is -0.15%. The difference is 1.21% (t=1.88), comparable with those for the entire stock sample (Table II).

For the stocks with option listing, the number of stocks in each decile ranges from 159 to 213. Therefore the size of this subsample is slightly smaller than that of the subsample without any option listing. Within this subsample, the return to the equal-weighted D1 portfolio is 0.93% and the return to the D10 portfolio is -0.45%. The difference is 1.37% and the t-statistic is 1.59. Although the t-statistic is weaker than that for the stocks without option listing, the magnitude of the bottom-top return difference is quite similar. An untabulated test suggests that the difference in the bottom-top return difference between the two subsamples is not statistically significant. Therefore, one can still conclude that option listing does not significantly mitigate the IVOL anomaly.

The results in Table V and Table II (for the option trading subsample) agree on one aspect – that options do not mitigate the anomaly. The difference is that stocks analyzed in Table II not only have option listing, but also have actively traded options. It appears that active option trading creates an additional effect to intensify the anomaly. This is a rather intriguing outcome. In the next section, we further analyze a hypothesis that is consistent with this result.

III.B. Informed Option Trading and the IVOL Anomaly

There are two possible explanations for the outcome that option trading has no mitigating effect on the IVOL anomaly. The first is that option traders do not have private information and neither do they trade on the information contained in IVOL. While this hypothesis can explain why option trading fails to correct stock market pricing, it does not explain why the IVOL anomaly is even stronger among stocks with active option trading. A second explanation, which is the focus of our investigation, is that option traders have private information about which high IVOL stocks are particularly mispriced. For example, they may have strong information about a subset of high IVOL stocks that are more likely going to release negative earnings news, than high IVOL stocks in general. Therefore, heavy option trading by these investors is a signal of existence of strong private information. Further, they execute the trades effectively to hide their private information, without significantly impact on either the option prices or underlying stock prices. As a consequence, stocks with options traded by these privately-informed investors exhibit a stronger IVOL anomaly. We refer to this as the informed option trading hypothesis. Apparently this hypothesis suggests that the exacerbated IVOL anomaly among stocks with active option trading is due to a selection effect, not a causal effect, by option traders.

Under this hypothesis one will not be able to detect informed option trading from option prices. However, informed trading inevitably leaves traces in some measures of option trading activity – an insight developed by Easley, O'Hara, and Srinivas (1998). In this section we use two empirical measures of informed option trading to further test this hypothesis.

III.B.1. O/S As Measure of Informed Option Trading

Several studies have developed measures of informed option trading activity using option transaction data. For example, Easley et al. (1998) separately tally trades on calls and puts based on whether they are buyer initiated or seller initiated. They find that "good news trades" such as buying call options and selling put options are positively correlated with future stock returns while "bad news trades" such as selling calls and buying puts, are negatively correlated with future stock returns. Pan and Poteshman (2006) use data on option trades initiated by option purchasers to construct a put-call ratio, defined as buyer-initiated trades on puts divided by buyer-initiated trades on calls and puts combined. They find that this put-call ratio have long-lasting predictive power on stock returns. However, we do not have access to such transaction level data, and instead resort to two relative option trading activity measures that can be constructed using the OptionMetrics data. The upside of using the publicly available data to measure informed option trading is that it bears directly to the issue of market efficiency.

Our first measure of informed option trading activity follows a recent study, Roll, Schwartz, and Subrahmanyan (2009). They construct a measure O/S, which is the ratio of trading volume for all option on an underlying stock to the stock trading volume. It could be argued that on an ex ante basis, O/S can be viewed as a proxy for either informed trading or dispersion of option traders' opinions (Choy and Wei 2009). Their conclusion that O/S is indicative of informed option trading is based on the empirical evidence that O/S is positively related to the magnitude of stock returns around subsequent earnings announcement, after controlling for factors that proxy for dispersion of investor opinions.

To implement this measure, in each month, we calculate the total number of contracts of all options traded for a stock, and then divide by the total number of shares traded in the stock market on that stock during the month. Since stock trading volume for NASDAQ stocks is reported differently that that reported for NYSE-AMEX stocks, we scale down NASDAQ stock trading volume by a factor of 0.7 (see, e.g., Anderson and Dyl 2007) before using it as the denominator in O/S.

To see how informed option trading makes a difference in the magnitude of the IVOL anomaly, we classify all stocks with valid O/S measure from the entire sample into three groups based on O/S. We also retain stocks' IVOL decile rankings formed in the entire stock sample. Independent double-sort on IVOL and O/S results in 30 equal-weighted stock portfolios.

Panel A of Table VI reports the number of stocks, average returns, and the Carhart four-factor alphas to each of the portfolios. Among stocks in the lowest O/S tercile, the numbers of stocks in IVOL decile ranges from 40 to 84. The bottom-top IVOL decile difference in stock return is 0.71%, and the difference in alpha is 0.27%, both positive but statistically insignificant.

Among the middle O/S tercile, the numbers of stocks across IVOL deciles are between 52 and 68. The bottom-top return difference is 1.20% and the alpha difference is 0.79%. The t-statistic for the return difference is insignificant but the t-statistic for alpha becomes significant. Finally, among the highest O/S tercile, the numbers of stocks in IVOL deciles vary between 47 and 70. The bottom-top difference in return is 1.89% and that in alpha is 1.40%. Both are statistically significant. Therefore, the higher the O/S, the stronger the anomaly.

It is also interesting to note that the difference in the magnitude of the IVOL anomaly across the three O/S groups is mainly due to the difference in returns to the high IVOL stocks. Returns to the bottom IVOL deciles across the three O/S groups are similar: 0.99%, 0.97%, and 0.85% respectively. On the other hand, returns to the top IVOL deciles across the three O/S groups decrease dramatically: 0.29%, -0.23%, and -1.04% for the low, medium, and high O/S terciles respectively. This suggests that the private information possessed by option traders is mainly concentrated on stocks with high IVOL.

Trading activities on calls and puts have different information about future stock returns. If investors have private information about high returns to certain stocks, they will likely buy calls on these stocks. If they have private information about low returns to certain stocks, they will likely buy puts. Consequently, private information on low-IVOL stocks should mainly be reflected by trading volume in calls, while private information on high-IVOL stocks should mainly be revealed by trading volume in puts. Following this intuition we construct two additional measures: call O/S and put O/S. Call O/S is the total number of call contracts traded during a month on the stock, divided by the monthly stock trading volume. Similarly, put O/S is the total number of put contracts traded during a month divided by the monthly stock trading volume. Again, stock trading volume for NASDAQ stocks is adjusted by a factor of 0.7.

Panel B of Table VI reports numbers of stocks, returns, and alphas for stocks classified jointly by IVOL, call O/S and put O/S. We keep the IVOL decile ranking formed in the entire stock sample. For low-IVOL stocks in deciles D1 to D5, we further them into three groups based on call O/S via an independent sort. For high IVOL stocks in deciles D6 to D10, we further classify them into three groups based on put O/S via an independent sort.

For stocks in the low-IVOL deciles, there is a small decline in returns and alphas as we move from low call O/S to high call O/S groups. For example, for the bottom IVOL decile (D1), the returns are 1.04%, 0.91%, and 0.82% for the low, medium, and high call O/S groups. By contrast, there is a more discernible decline in returns for stocks in the high-IVOL deciles as we move from low put O/S to high put O/S groups. For the top IVOL decile (D10), the returns are 0.25%, -0.52%, and -0.87% respectively for low, medium, and high put O/S groups. This confirms the intuition that put option trading activity captures the intensity of option traders' private information about high IVOL stocks.

III.B.2. OI/S As Measure of Informed Option Trading

Our second measure of informed option trading is based on option open interest. Open interest measures option positions created through past trading that are not yet liquidated. Thus intuitively open interest provides a better summary of investors' belief about future stock returns than past option trading volume, and presumably a proportion of investors open positions are supported by informed beliefs. There is also empirical evidence that open interest captures private information prior to earnings announcement (Amin and Lee 1997), lending support to the use of open interest as an indication of informed option trading.

We construct OI/S, which is the sum of all open interests on the last trading day of a month on all options of an underlying stock, divided by the exchange-adjusted monthly stock trading volume. If open interest for an option is missing on the last trading day, we use the last valid open interest observation during the month, as long as that day is within five trading days from the month-end.

We then perform independent double-sort on IVOL and OI/S to classify stocks into 30 groups, in a way similar to those based on IVOL and O/S in the above section. Panel A of Table VII reports numbers of stocks, returns, and alphas to the stock portfolios formed on both IVOL and OI/S. The patterns are similar to those obtained using O/S (reported in Panel A of Table VI), and are even stronger. The return difference between the bottom and top IVOL deciles is increasing in OI/S. Among the low OI/S group, the bottom-top IVOL decile return difference is 0.64%. It increases to 1.69% for the medium OI/S group, and to 2.11% for the high OI/S group. Alphas exhibit a similarly strong pattern. Therefore, high intensity of informed option trading as measured by OI/S is associated with intensified mispricing of underlying stocks.

Further, the return difference across OI/S groups is mainly caused by the return difference in the high IVOL deciles. For stocks in the bottom IVOL deciles, returns are similar across the three OI/S groups, at 0.85%, 1.05%, and 0.90% respectively. By contrast, for stocks in the top IVOL deciles, returns across the OI/S groups drop dramatically: from 0.21% for the low OI/S group, to -0.63% for the medium OI/S group, and to -1.22% for the high OI/S group. Therefore, private information captured by OI/S is mainly concentrated on the high IVOL stocks.

We also construct call OI/S and put OI/S in a way similar to call O/S and put O/S. Specifically, call OI/S is the sum of all open interests on call options of an underlying stock divided by monthly exchange-adjusted stock trading volume, and put OI/S is the sum of all open interests on put options of an underlying stock divided by monthly exchange-adjusted stock trading volume. In Panel B of Table VII, we classify stocks in IVOL deciles D1 to D5 into three groups via an independent sort on call OI/S, and classify stocks in IVOL deciles D6 to D10 into three groups via an independent sort on put OI/S. Returns and alphas exhibit relatively small differences across the three call OI/S groups for each of the five low IVOL deciles. On the other hand, returns and alphas have large differences across the three put OI/S groups for each of the five high IVOL deciles. In particular, for the top IVOL decile, return to the low put OI/S group is 0.19%, while return to the medium put OI/S group is -0.40% and return to the high put OI/S group is -1.38%. This again confirms that option traders' private information is mainly in the form of low returns to some high IVOL stocks and can be readily captured by put option trading activity.

III.B.3. Multivariate Regressions

We perform the following Fama-MacBeth regressions to examine the effect of informed option trading on the IVOL anomaly.

$$\begin{aligned} R_{it+1} &= b_0 + b_1\text{Ln}(\text{SIZE}_{it}) + b_2\text{BM}_{it} + b_3\text{MOM}_{it} + b_4 R_{it} + b_5\text{IVOL}_{it} \\ &\quad + b_6\text{Ln}(\text{O/S}_{it}) * \text{IVOL}_{it} + b_7\text{Ln}(\text{TURN}_{it}) * \text{IVOL}_{it} + e_{it+1} \end{aligned} \tag{4}$$

where R_{it+1} is stock return during month t+1, SIZE_{it} is market capitalization at the end of month t, BM_{it} is the book-to-market ratio based on market capitalization at the end of month t and book value for the fiscal year reported by the end of month t, MOM_{it} is stock return during the period from month t-12 to month t-1, and R_{it} is stock return during month t. IVOL_{it} is the idiosyncratic volatility measured for month t, and O/S_{it} is the relative option trading activity measure of Roll et al. (2009). Finally, TURN_{it} is stock trading turnover, measured as the number of shares traded during month t divided by total shares outstanding. NASDAQ trading volume is again adjusted by a factor of 0.7. The regressions are performed in each month and we obtain time series averages of the estimated coefficients and their time series t-statistics. We also perform the above regression by replacing O/S_{it} with the second relative option trading activity measure OI/S_{it}.

The coefficients for $\text{Ln}(\text{O/S}_{it})$*$\text{IVOL}_{it}$ and for $\text{Ln}(\text{OI/S}_{it})$*$\text{IVOL}_{it}$ are the main object of interest. We include the product term $\text{Ln}(\text{TURN}_{it})$*$\text{IVOL}_{it}$ as a control because of the concern that both O/S and OI/S use stock trading volume as the denominator. Stock trading volume per se might negatively related to the magnitude of the IVOL anomaly, because the IVOL anomaly might be weaker among more liquid stocks.

The results are reported in Table VIII. As it turns out, the coefficients for $\text{Ln}(\text{O/S}_{it})$*$\text{IVOL}_{it}$ and $\text{Ln}(\text{OI/S}_{it})$*$\text{IVOL}_{it}$ are significantly negative, regardless of whether or not the control variable $\text{Ln}(\text{TURN}_{it})$*$\text{IVOL}_{it}$ is present.

We also check the correlations of stock trading turnover with O/S and OI/S. They are relatively low: the correlation between O/S and the inverse of stock trading turnover is 0.13, and that between O/S and the inverse of stock trading volume is 0.14. In further (untabulated) analysis, we use a double-sorting procedure to control for the effect of stock trading turnover when examining the relation between relative option trading measures and the magnitude of the IVOL anomaly, and continue to find strong results.

III.C. Private Information in the Form of Future Earnings

A common type of private information possessed by option traders is about the future earnings that are soon to be announced. More concretely, option traders' private information about the low returns to some high IVOL stocks is likely in the form of low earnings or negative earnings surprises for the coming quarters. We check if this is the case.

In Table IX, we report the average return on equity (ROE) and standard unexpected earnings (SUE) for stock portfolios double-sorted by IVOL and one of the two relative option trading activity measures. Specifically, in each month, we retain the IVOL decile ranking from the entire stock sample and independently sort stocks into three groups based on O/S (or OI/S). This results in 30 double-sorted portfolios. ROE and SUE are measured for the fiscal quarter reported within three months after the portfolio formation month. ROE is the net income divided by beginning of quarter book value of equity. SUE is defined as follows:

$$SUE = \frac{\Delta\text{EPS} - u(\Delta\text{EPS})}{\sigma(\Delta\text{EPS})} \tag{5}$$

where ΔEPS is the change of earnings per share (EPS) from four quarters ago, $u(\Delta\text{EPS})$ and $\sigma(\Delta\text{EPS})$ are respectively the mean and standard deviation of ΔEPS during the past 8 quarters. We require a minimum of past 4 quarterly observations of ΔEPS for the computed SUE to be valid.

From the table, within each group sorted on relative option trading activity, stocks with higher IVOL have lower ROE and SUE, a pattern consistent with that reported by Jiang et al. (2009). We also calculate the difference in ROE and SUE between the top and bottom IVOL deciles within each relative option trading activity group. To address the overlapping data issue in measuring future earnings, the t-statistics are computed using the Newey-West covariance estimator with three lags. As it turns out, the differences in ROE and SUE are always highly significant as suggested by the t-statistics.

Further, the differences in ROE and SUE between the top and bottom IVOL deciles increase (become more negative) as we move from the low O/S (or OI/S) group to the high O/S (OI/S) group. Therefore, relative option trading activity magnifies the negative relation between IVOL and future earnings. This is quite straightforward evidence of private information in option trading.

To sum, the results obtained in Table VI to Table IX are consistent with the hypothesis that some investors trade in the option market with private information about stock returns and among high IVOL stocks, informed option trading is concentrated on the ones with particularly low returns. An additional implication is that informed option traders have executed their trades effectively to minimize price impact. On the flip side, these results suggest that other investors in both the option market and the stock market fail to take notice of such private information, despite that the two measures of relative option trading activity, as well as IVOL, are observable to all investors. In other words, the first mechanism via which option trading may improve stock price efficiency (as described in Introduction) is not as effective as what one expects for an efficient market.

III.D. Option Trading Cost and Profitability of Synthetic Stock Strategies

We now turn to the effectiveness of the second mechanism – the advantage of using options to overcome short-sale constraints in the stock market. Presumably, stocks with high idiosyncratic volatility are difficult to short and options can help. However, the option market has its own frictions. For example, option transaction costs are known to be high.[7] Vijh (1990) find that

[7]Another important friction in the option market is margin requirement for writing options; see Santa-Clara and Saretto (2009). On the other hand, there are advantages to the use of options, in addition to the ability to overcome short-sale constraint. For example, options offer leverage at essentially the riskfree rate, while margins in the stock market is often more limited and come at a higher financing cost.

price impact of large option trades is small; however, the bid-ask spreads for options are as high as those for NYSE stocks. Since option prices are much lower than underlying stock prices, this means that option bid-ask spreads as a fraction of option prices are several times higher than those for stocks. Also, fewer option trades occur inside the bid-ask spreads relative to stocks. A few recent studies, such as Mayhew (2002), find that option trading costs have come down substantially over time and traded prices more often occur inside the bid-ask spread in recent periods, likely due to competition. However, the magnitude of option bid-ask spreads remain high. High option trading costs may render it ineffective to use options to overcome short-sale constraints.

From the results in Section III.B., informed investors apparently trade on their private information using options. At least, this mechanism is working for them. Possibly, their information is concentrated on a small number of stocks but with high signal-to-noise ratio, and based on such concentrated information they can profit even after high option trading costs. However, the answer could be very different on the question of whether the IVOL-based trading strategy per se can be profitable. Put it in a more concrete way, the question is whether an investors aware of the IVOL anomaly, but without private information about future earnings, can profit from an option based trading strategy on the anomaly. The before-trading-cost profitability of the IVOL strategy is slightly above 1% per month, as suggested by numbers in Table II. Whether the strategy remains profitable after option trading cost is an important question.

Our analysis focuses on the bid-ask spread component of trading costs for the IVOL strategy based on synthetic stock positions. The profitability of this strategy, before trading cost, is already reported in Table IV. Trading cost estimation involves the following steps. First, for each synthetic stock position, we estimate the quoted option spread as a percentage of the underlying stock price (referred to as "percentage quoted spread"), for both the call and the put, when the positions are opened at the end of the portfolio formation month and when the positions are closed at the end of the holding month. Second, we compute the average percentage quoted spreads for each IVOL decile portfolio. Third, we assume a ratio of percentage effective spread to percentage quoted spread, ranging from 25% to 100%, and compute the percentage trading cost for each portfolio as one half of the average effective spread. Finally, net returns to the decile portfolios are calculated as the raw portfolio returns minus the percentage trading cost.

The results are reported in Table X. In Panel A, which reports percentage quoted spreads, a noted pattern is that the spreads increase monotonically from the low IVOL deciles to high IVOL deciles, at the beginning and at the end of the holding month. For the lowest IVOL decile, the average quoted spread is 0.36% for calls and 0.35% for puts at the beginning of the holding month, and 0.34% and 0.33% respectively at the end of the holding month. For the highest IVOL decile, the average quoted spreads are 1.19% and 1.22% for calls and puts at the beginning of the holding month, and 1.02% and 1.25% respectively at the end of the holding month. If the round-trip trading cost on an option is 50% of the round-trip quoted spreads, for the puts of the highest IVOL decile along it amounts to 1.24%, only slightly below the before-trading-cost D1-D10 synthetic return spread reported in Table IV.

Panel A also separately report the percentage quoted spreads for two subperiods, before and after 2004. The results show that the spreads have certainly decreased in the second subperiod; however even in this subperiod option quoted spreads remain quite high.

In Panel B, we report after-trading-cost synthetic returns to the IVOL deciles, under four different assumptions on the ratio of effective spread to quoted spread. The bottom-top return difference after trading cost is computed as the before-trading-cost synthetic returns (those reported in Table IV), minus one half of the effective spread for call at both beginning and end of the month, and minus one half of the effective spread for put at both beginning and end of the month. As it turns out, trading cost completely wipes out the paper profit of the synthetic stock strategy, even at a moderate assumption about the ratio of effective to quoted spread. For example, when the ratio of effective spread to quoted spread is 0.5, the resulting D1-D10 return is 0.17% (t=0.21) after trading cost.

A point can be made that the synthetic stock strategy in Panel B is not the optimal strategy in the presence of trading cost. We examine a few alternative implementation of the strategy to see if any of them can survive the trading cost. In Panel C, we report results of the strategy that holds the options until expiration. The before-trading-cost profit of this strategy is reported in Table VI. When options on individual stocks expire, option buyers can take physical delivery or deliver the underlying stocks. We make a simplifying assumption that the return to this strategy is the pre-trading-cost return (those reported in Table VI) minus one half of the percentage effective spreads for calls and puts only at the beginning of the holding month only.[8]

The results suggest that this option-based strategy is not significantly profitable after trading cost. For example, when the effective/quoted spread ratio is 0.5, the strategy yields 1.33% per month after trading cost, with an insignificant t-statistic (1.31). Only under the most optimistic assumption on the ratio of effective to quoted spread (0.25), the profit becomes significantly positive after trading cost.

Overall, the results from this part of analysis suggest that trading cost is substantial in the option market. After trading cost, it is not profitable to synthetically trade on the IVOL anomaly. Therefore, using options to overcome the short-sale constraint and correct market anomalies may not be as effective as popularly perceived.

IV. Conclusions

In this study, we investigate the informational role of options in the context of the idiosyncratic volatility anomaly. Our findings are perhaps to the opposite of a conventional belief: active option trading fails to mitigate stock market mispricing associated with idiosyncratic volatility, but rather exacerbates it. Also strikingly, as evidence by returns to synthetic stock portfolios, option prices exhibit a very similar pattern of mispricing. We perform multiple variations in analysis to ensure the results are robust.

The results are intriguing, but not completely at odds with some versions of theoretical conjecture about the informational role of options. In particular, privately-informed traders may choose the option market instead of the stock market as venue for their trading, and their

[8]Actually, this assumption underestimates the total trading costs by ignoring the stock trading cost involved at option expiration. For example, when call option buyers take delivery of underlying stocks, they still have to incur a cost to sell the delivered shares.

private information may not be immediately reflected into option prices when they execute the trades effectively. As a consequence, option trading activities may reveal the trace of private information, but mispricing in the option prices or stock prices is not immediately reduced.

We test this hypothesis by constructing two proxies for the presence of informed option trading, one based on the relative trading volume of options and stocks and the other based on the ratio of option open interest to the stock trading volume. Empirical evidence based on these two measures is consistent with the informed option trading hypothesis: the relations of IVOL with future stock returns and with future earnings are both stronger among stocks with higher measures of informed option trading. Finally, we find that option trading costs are substantial, to the extent that they virtually wipe out all paper profits from option based synthetic stock strategies that are intended to overcome the short-sale constraints.

Appendix: Early Exercise Premium Estimation using the CRR Binomial Tree Method

The appendix explains the procedures to estimate early exercise premium (EEP) of American options, using a binomial tree method (Cox, Ross, and Rubinstein 1979). At both current month and next month, we estimate EEPs for both call and put options.

1. Provided that implied volatility is available from OptionMetrics Ivy Database, we obtain the annualized riskfree rate and annualized dividend yields which correspond to the current and next month option observation dates. The riskfree rates are available from the WRDS Fama-French factors database. Regarding the annualized dividend yield, year by year we add up all possible dividend amounts which need to be adjusted for stock splitting. We then divide the summed dividend amounts by stock prices at the first trading dates of the year to estimate the annualized dividend yields.

2. Provided that other input variables such as strike price, maturity, and stock price, we plug in the following input variables into the CRR binomial tree:

   - Annualized dividend yield
   - Annualized riskfree rate
   - Current month (or next month) stock prices
   - Strike prices
   - Implied volatility (provided by OptionMetrics)
   - Days to maturity (DTM): one DTM is between current date and option expiry, the other DTM is between next month and expiry date.

3. We choose 50 as the number of sub-period from current (or next month) until maturity. For example, if DTM is 20 days from current date, the subperiod is 20/50 days.

4. For both current months' and next months' American call and put prices, we repeat the CRR tree optimization until squared differences between market prices and CRR prices become less than 1e-15.

5. Choose the early exercise premium values which are the difference between the market prices and the European option prices based on the CRR tree method.

If we encounter a problem of missing implied volatility, we circumvent it by applying non-linear regression models such as Dumas, Fleming, and Whaley (1998). Since around 20% of implied volatilities are missing from OptionMetrics due to out-of-the-money (OTM), we first should estimate the volatilities so that we can use them to conduct CRR binomial tree method. The non-linear regression is expressed as follows:

$$\begin{aligned}\operatorname{Im} pVol_{i,t} &= a_{0,t} + a_{1,t}(S/X)_{i,t} + a_{2,t}(S/X)^2_{i,t} + a_{3,t}((T-t)/365)_i + a_{4,t}((T-t)/365)^2_i \\ &\quad + a_{5,t}(S/X)_{i,t}((T-t)/365)_i + \epsilon_{i,t}\end{aligned} \tag{6}$$

where $\mathrm{Im}\, PVol_{i,t}$ denotes the Implied volatility of the stock i at the next month t, (S/X) define the moneyness of the option, $((T-t)/365)$ is the days to expiry, and $\epsilon_{i,t}$ is the error terms of the regression (6).

We obtain the coefficient estimates $a_{0,t}, a_{1,t}, a_{2,t}, a_{3,t}, a_{4,t}$ and $a_{5,t}$ by regressing the non-missing Implied volatility on the independent variable sets as described in (6), then retain the coefficient estimates. Re-plugging in equation (6) the independent variable sets enables us to estimate the fitted value with which we can conduct CRR binomial tree method. We, then, recover American and European option prices.

Once we obtain the CRR-based early exercise premium using , and in the regression (6) to estimate the missing Implied volatility. We can adjust the American option prices and obtain the synthetic stock prices at both current and next month, as shown in the following equation:

$$S_{i,t} = [c_{i,t+1} - p_{i,t+1} - (EEP_{c,i,t+1} - EEP_{p,i,t+1})] + D_{i,t+1,\tau+1} + X_i e^{-r_{t+1}(\tau-t-1)}$$

subsequently the EEP-adjusted synthetic stock returns is given by:

$$R_{i,t} = \frac{S_{i,t+1}}{S_{i,t}} - 1$$

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Table I
Summary Statistics on Idiosyncratic Volatility

This table reports the summary statistics of idiosyncratic volatility (IVOL) for the entire stock sample during the period from January 1996 to September 2008, and during the three subperiods: 1996-2000, 2001-2004, and 2005-2008. The entire stock sample consists of all common stocks with price no less than $5 at the end of the portfolio formation month. N is the average number of firms in each month during the period or subperiod. IVOL is the standard deviation of the estimated residuals from regressing daily stock returns onto contemporaneous daily market returns as well as three lagged market returns. We calculate both the mean and median of IVOL across all stocks in a month and then average the statistics over the entire period and over the subperiods.

Period	N	Mean IVOL	Median IVOL
Whole Sample Period			
1996-2008	4,354	2.41	2.37
Three Subperiods			
1996-2000	5,284	2.88	2.66
2001-2004	3,777	2.22	2.12
2005-2008	3,755	2.01	1.76

Table II
Stock Portfolios Sorted on Idiosyncratic Volatility: The Entire Stock Sample and Option Trading Subsample

This table reports the average IVOL, monthly returns and the monthly Carhart (1997) four-factor alphas to equal-weighted decile stock portfolios sorted on IVOL, in the entire sample of common stocks and in the option trading subsample. The entire stock sample consists of all common stocks with price no less than $5 at the end of the portfolio formation month. The option trading subsample consists of common stocks from the entire stock sample that meet the following selection criteria: there is at least a pair of call and put options on the stock, expiring in two months after the portfolio formation month, having the same strike price, and having positive trading volume, positive open interest, and valid quotes on the last trading day of the formation month. IVOL is the standard deviation of the estimated residuals from regressing daily stock returns onto contemporaneous daily market returns as well as three lagged market returns. When forming IVOL decile portfolios within the option trading subsample we use the IVOL breakpoints obtained for the entire stock sample. D1 (D10) is the portfolio of stocks with the lowest (highest) IVOL. D1-D10 is the difference between portfolio D1 and portfolio D10. N is the average number of stocks each month each decile. t-statistics of the return difference and alpha difference are reported in parenthesis. All returns and alphas are in percentage points. The portfolio formation period is from January 1996 through September 2008.

IVOL	Entire Stock Sample				Option Trading Subsample			
Decile	N	IVOL	RET	α	N	IVOL	RET	α
D1 (L)	433	0.74	0.96	0.33	28	0.80	0.96	0.13
D2	435	1.12	0.98	0.26	36	1.11	0.99	0.22
D3	435	1.38	0.95	0.22	37	1.36	1.12	0.31
D4	436	1.63	0.9	0.16	36	1.62	1.07	0.21
D5	436	1.90	0.86	0.10	37	1.88	0.79	0.01
D6	436	2.21	0.88	0.15	37	2.19	1.16	0.35
D7	436	2.57	0.7	-0.04	37	2.54	0.72	-0.08
D8	436	3.03	0.56	-0.13	37	3.00	0.83	0.16
D9	436	3.71	0.28	-0.34	36	3.69	0.34	-0.09
D10 (H)	435	5.79	-0.27	-0.83	36	5.74	-0.78	-1.24
D1-D10			1.23	1.16			1.74	1.36
			(1.72)	(4.40)			(2.08)	(3.00)

Table III
Synthetic Stock Returns to Portfolios Sorted on Idiosyncratic Volatility

This table reports the average synthetic returns with and without EEP adjustment, and the corresponding four-factor alphas for decile portfolios sorted on IVOL, within the option trading subsample. The option trading subsample consists of common stocks from the entire stock sample that meet the following selection criteria: there is at least a pair of call and put options on the stock, expiring in two months after the portfolio formation month, having the same strike price, and having positive trading volume, positive open interest, and valid quotes on the last trading day of the formation month. Synthetic stock return without EEP adjustment is return to a synthetic stock position that involves buying a call, selling a put with the same maturity and strike price, and holding risk-free assets amounting to the present value of strike price and expected dividends. The EEP-adjusted synthetic stock return is the synthetic stock return adjusting for the early exercise premium, following the CRR procedure described in the Appendix. The IVOL decile ranking for a stock is based on the IVOL decile break-points of the entire stock sample. D1 (D10) is the portfolio of actual stocks with the lowest (highest) idiosyncratic volatility. D1-D10 is the difference between D1 and D10 portfolios. N is the average number of stocks for each decile in each month. t-statistics are reported in parenthesis. All returns and alphas are in percentage points. The portfolio formation period is from January 1996 through September 2008.

IVOL	Without EEP Adjustment		With EEP Adjustment	
Decile	Synthetic RET	α	Synthetic RET	α
D1 (L)	0.95	0.14	0.98	0.17
D2	0.96	0.20	0.98	0.22
D3	1.09	0.30	1.11	0.32
D4	0.96	0.12	0.98	0.13
D5	0.76	-0.02	0.78	0.00
D6	1.08	0.28	1.09	0.30
D7	0.64	-0.13	0.66	-0.11
D8	0.79	0.13	0.81	0.15
D9	0.28	-0.15	0.29	-0.14
D10 (H)	-0.73	-1.18	-0.72	-1.17
D1-D10	1.68	1.32	1.70	1.33
	(2.05)	(2.91)	(2.07)	(2.96)

Table IV
Returns and Synthetic Returns to Portfolios Sorted on Idiosyncratic Volatility: Holding Until Expiration

This table reports average stock returns and synthetic returns (without EEP adjustment) for decile stock portfolios sorted on IVOL, within the option trading subsample. The option trading subsample consists of common stocks from the entire stock sample that meet the following selection criteria: there is at least a pair of call and put options on the stock, expiring in two months after the portfolio formation month, having the same strike price, and having positive trading volume, positive open interest, and valid quotes on the last trading day of the formation month. The stock returns and the synthetic stocks without EEP adjustment are calculated for the holding period from the end of the portfolio formation month until the date of option expiration, i.e., the third Friday of the second month after portfolio formation. Synthetic stock return is return to a synthetic stock position that involves buying a call, selling a put with the same maturity and strike price, and holding risk-free assets amounting to the present value of strike price and expected dividends. The IVOL decile ranking for a stock is based on the IVOL decile breakpoints of the entire stock sample. D1 (D10) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. D1-D10 is the difference between the D1 and D10 portfolios. IVOL is the standard deviation of the estimated residuals from regressing daily stock returns onto contemporaneous daily market returns as well as three lagged market returns. N is the average number of stocks for each decile. t-statistics are reported in parenthesis. All returns and synthetic returns are in percentage points. The portfolio formation period is from January 1996 through September 2008.

IVOL Decile	N	IVOL	Stock RET	Synthetic RET
D1 (L)	32	0.80	1.73	1.72
D2	41	1.10	1.65	1.55
D3	42	1.36	1.87	1.85
D4	41	1.61	1.83	1.81
D5	42	1.88	1.40	1.45
D6	42	2.18	1.70	1.73
D7	42	2.53	1.50	1.54
D8	43	2.99	1.51	1.62
D9	42	3.67	0.59	0.73
D10 (H)	43	5.72	-0.62	-0.38
D1-D10			2.35	2.10
			(2.31)	(2.07)

Table V
Stock Portfolios Sorted on Idiosyncratic Volatility: Stocks with Options and Stocks without Options

This table reports average stock returns and Carhart four-factor alphas for equal-weighted decile portfolios sorted on idiosyncratic volatility (IVOL) in two subsamples of stocks. The first subsample consists of all stocks within the entire stock sample that have option listings in the portfolio formation month. The second subsample consists of all stocks within the entire stock sample that do not have any option listings in the portfolio formation month. IVOL is the standard deviation of the estimated residuals from regressing daily stock returns onto contemporaneous daily market returns as well as three lagged market returns. The IVOL decile ranking for a stock is based on the IVOL decile breakpoints of the entire stock sample. D1 (D10) is the portfolio of actual stocks with the lowest (highest) IVOL. D1-D10 is the difference in monthly returns between D1 and D10. N is the average number of stocks in each decile. t-statistics are reported in parenthesis. All returns and alphas are in percentage points. The portfolio formation period is from January 1996 to September 2008.

IVOL	Stocks with Option Listing				Stocks without Option Listing			
Decile	N	IVOL	RET	α	N	IVOL	RET	α
D1 (L)	182	0.77	0.93	0.15	251	0.71	1.06	0.47
D2	213	1.11	0.95	0.16	222	1.12	1.03	0.31
D3	208	1.37	0.81	0.01	227	1.38	1.12	0.39
D4	204	1.62	0.84	0.03	232	1.63	0.95	0.20
D5	200	1.89	0.82	-0.03	236	1.9	0.93	0.18
D6	197	2.19	0.75	-0.05	239	2.21	1.07	0.35
D7	194	2.55	0.52	-0.24	242	2.57	0.88	0.10
D8	191	3.01	0.35	-0.32	245	3.03	0.78	0.01
D9	181	3.68	-0.01	-0.57	255	3.72	0.48	-0.28
D10 (H)	159	5.55	-0.45	-0.78	276	5.90	-0.15	-0.96
D1-D10			1.37	0.94			1.21	1.43
			(1.59)	(3.28)			(1.88)	(5.16)

Table VI
Portfolios Sorted On Idiosyncratic Volatility and O/S

This table reports the monthly average stock returns and the Carhart four-factor alphas for equal-weighted stock portfolios double-sorted on idiosyncratic volatility (IVOL) and the relative option trading measure O/S. IVOL is the standard deviation of the estimated residuals from regressing daily stock returns onto contemporaneous daily market returns as well as three lagged market returns. N is the average number of stocks for each decile. O/S is the ratio of option trading volume to the underlying stock trading volume during the portfolio formation month. In Panel A, stocks with option trading are independently sorted into deciles based on idiosyncratic volatility, and into terciles based on O/S. In Panel B, stocks in the bottom five IVOL deciles are double-sorted by IVOL and Call O/S, while stocks in the top five IVOL deciles are double-sorted by IVOL and Put O/S. Call O/S (Put O/S) is the ratio of call (put) option trading volume to stock trading volume. N is the average number of stocks in each portfolio. Returns and alphas are in percentage points. The sample period is from January 1996 through December 2008.

Panel A: Stock Portfolios Sorted by IVOL and O/S									
	Low O/S			Medium O/S			High O/S		
IVOL Decile	N	RET	α	N	RET	α	N	RET	α
D1(L)	80	0.99	0.23	52	0.97	0.13	47	0.85	0.08
D2	84	1.01	0.22	67	0.97	0.11	58	0.78	0.05
D3	76	0.89	0.05	68	0.74	-0.09	62	0.74	0.06
D4	70	0.95	0.09	67	0.74	-0.02	64	0.75	-0.04
D5	65	1.14	0.22	66	0.93	0.01	66	0.36	-0.32
D6	61	0.91	0.01	65	0.71	0.02	70	0.66	-0.16
D7	57	0.47	-0.35	66	0.59	-0.35	70	0.39	-0.13
D8	54	0.57	-0.14	66	0.42	-0.27	70	0.07	-0.54
D9	49	0.42	-0.20	63	0.19	-0.48	68	-0.48	-0.85
D10(H)	40	0.29	-0.04	57	-0.23	-0.67	61	-1.04	-1.32
D1-D10		0.71	0.27		1.20	0.79		1.89	1.40
		(0.81)	(0.68)		(1.35)	(2.39)		(2.19)	(3.53)

Panel B: Stock Portfolios Sorted by IVOL, Call O/S, and Put O/S									
	Low O/S			Medium O/S			High O/S		
IVOL Decile	N	RET	α	N	RET	α	N	RET	α
Bottom Five IVOL Deciles Sorted By Call O/S									
D1 (L)	79	1.04	0.30	52	0.91	0.10	46	0.82	0.04
D2	84	0.98	0.16	68	0.99	0.15	57	0.83	0.09
D3	77	0.86	0.04	68	0.77	-0.04	60	0.75	0.05
D4	70	0.93	0.03	67	0.78	-0.01	63	0.79	0.06
D5	66	1.03	0.15	66	0.88	-0.09	65	0.55	-0.12
Top Five IVOL Deciles Sorted By Put O/S									
D6	59	0.87	-0.06	61	0.78	0.09	65	0.6	-0.17
D7	55	0.76	-0.12	62	0.49	-0.34	65	0.35	-0.2
D8	54	0.58	-0.13	62	0.25	-0.42	64	0.21	-0.3
D9	52	0.47	-0.19	60	0.14	-0.37	60	-0.52	-0.97
D10 (H)	44	0.25	-0.16	56	-0.52	-0.79	54	-0.87	-1.00
D1-D10		0.79	0.46		1.43	0.89		1.69	1.04
		(0.78)	(0.91)		(1.37)	(2.33)		(1.99)	(2.21)

Table VII
Portfolios Sorted On Idiosyncratic Volatility and OI/S

This table reports the monthly average stock returns and the Carhart four-factor alphas for equal-weighted stock portfolios double-sorted on idiosyncratic volatility (IVOL) and the relative option trading measure OI/S. IVOL is the standard deviation of the estimated residuals from regressing daily stock returns onto contemporaneous daily market returns as well as three lagged market returns. N is the average number of stocks for each decile. OI/S is the ratio of option open interest to the underlying stock trading volume during the portfolio formation month. In Panel A, stocks with option trading are independently sorted into deciles based on idiosyncratic volatility, and into terciles based on OI/S. In Panel B, stocks in the bottom five IVOL deciles are double-sorted by IVOL and Call OI/S, while stocks in the top five IVOL deciles are double-sorted by IVOL and Put OI/S. Call OI/S (Put OI/S) is the ratio of call (put) option open interest to stock trading volume. N is the average number of stocks in each portfolio. Returns and alphas are in percentage points. The sample period is from January 1996 through December 2008.

Panel A: Stock Portfolios Sorted by IVOL and O/S									
	Low OI/S			Medium OI/S			High OI/S		
IVOL Decile	N	RET	α	N	RET	α	N	RET	α
D1(L)	66	0.85	0.08	55	1.05	0.28	60	0.90	0.11
D2	73	0.96	0.07	68	0.98	0.26	71	0.88	0.11
D3	69	0.88	0.03	67	0.78	-0.14	70	0.75	0.14
D4	65	0.89	0.07	67	0.85	-0.04	70	0.75	0.02
D5	64	1.11	0.2	66	0.95	0.12	69	0.39	-0.38
D6	61	0.97	0.02	67	0.75	-0.10	69	0.55	-0.12
D7	60	0.45	-0.4	66	0.52	-0.23	67	0.50	-0.16
D8	60	0.71	-0.05	66	0.32	-0.32	64	0.03	-0.57
D9	60	0.58	-0.08	63	-0.06	-0.50	57	-0.52	-1.18
D10(H)	62	0.21	-0.24	55	-0.63	-0.79	42	-1.22	-1.69
D1-D10		0.64	0.31		1.69	1.07		2.11	1.80
		(0.70)	(0.95)		(1.97)	(3.02)		(2.33)	(3.95)

Panel B: Stock Portfolios Sorted by IVOL, Call OI/S, and Put OI/S									
	Low OI/S			Medium OI/S			High OI/S		
IVOL Decile	N	RET	α	N	RET	α	N	RET	α
Bottom Five IVOL Deciles Sorted By Call OI/S									
D1 (L)	65	0.87	0.09	56	1.06	0.20	60	0.87	0.15
D2	72	0.93	0.08	69	1.04	0.23	70	0.86	0.13
D3	70	0.85	-0.02	67	0.82	-0.06	70	0.76	0.09
D4	66	0.91	0.04	67	0.85	0.01	69	0.75	0.02
D5	64	1.07	0.13	66	0.97	0.08	68	0.43	-0.24
Top Five IVOL Deciles Sorted By Put OI/S									
D6	59	0.99	0.02	65	0.58	-0.16	69	0.66	-0.09
D7	59	0.51	-0.42	65	0.47	-0.16	66	0.5	-0.2
D8	60	0.51	-0.25	65	0.43	-0.18	62	0.07	-0.47
D9	60	0.54	-0.09	63	0.11	-0.40	55	-0.67	-1.21
D10 (H)	61	0.19	-0.16	55	-0.40	-0.69	40	-1.38	-1.66
D1-D10		0.68	0.25		1.46	0.89		2.25	1.81
		(0.83)	(0.76)		(1.84)	(2.33)		(2.55)	(3.82)

Table VIII
Idiosyncratic Volatility, Relative Option Trading Activity, and Stock Returns: Fama-MacBeth Regressions

This table reports the result from the following Fama-MacBeth regressions. The dependent variable is stock return during month t+1, R_{t+1}. The explanatory variables include log market capitalization (Ln(SIZE)), book-to-market ratio (BM), past stock returns from month t-12 to month t-1 (MOM), stock return during month t, R_t, idiosyncratic volatility (IVOL), the product term of Ln(O/S) (or Ln(OI/S)) and IVOL, and the product term of Ln(TURN) and IVOL. O/S is the option trading volume relative to stock trading volume, OI/S is the option open interest relative to stock trading volume, and TURN is stock trading turnover. SIZE, BM, IVOL, O/S, OI/S, and TURN are all measured in month t. Stock returns are in percentage point. The cross-sectional regressions are performed monthly. The coefficients are averaged over sample months. The t-statistics are computed using the Newey-West procedure with 3 lags. Adj. R^2 is the average adjusted R-squares of the monthly regressions. The sample period is from January 1996 to September 2008.

explanatory variables	(1)	(2)	(3)	(4)
Intercept	6.50	7.25	7.15	7.64
	(3.51)	(4.02)	(3.91)	(4.31)
Ln(SIZE)	-0.09	-0.14	-0.12	-0.14
	(-0.52)	(-1.21)	(-1.05)	(-1.28)
BM	0.38	0.37	0.41	0.40
	(2.17)	(2.02)	(2.28)	(2.18)
MOM	0.42	0.32	0.38	0.31
	(1.31)	(1.03)	(1.18)	(0.97)
R_t	-0.33	-0.25	-0.44	-0.37
	(-0.26)	(-0.19)	(-0.36)	(-0.29)
IVOL	-81.55	-89.02	-64.71	-64.95
	(-3.94)	(-3.96)	(-3.95)	(-3.52)
Ln(O/S)*IVOL	-10.31	-10.44		
	(-2.74)	(-2.79)		
Ln (OI/S)*IVOL			-9.69	-9.98
			(-2.44)	(-2.27)
Ln(TURN)*IVOL		8.58		5.55
		(1.11)		(0.71)
Adj. R^2 (%)	6.38	6.84	6.49	6.96

Table IX
Portfolios Sorted On Idiosyncratic Volatility and Relative Option Trading Activity Measures: Future Earnings

This table reports return on equity (ROE) and standardized unexpected earnings (SUE) for stock portfolios double-sorted on idiosyncratic volatility and one of the two relative option trading activity measures: O/S (Panel A) and OI/S (Panel B). In each month, stocks are double-sorted by IVOL and by O/S (OI/S) into 10×3 portfolios. ROE is return on equity for the fiscal quarter reported within the three months after portfolio formation. SUE is standardized unexpected earnings for the fiscal quarter reported within the three months after portfolio formation. ROE and SUE for individual stocks are averaged within each portfolio. t-statistics are computed using the Newey-West procedure with six lags. ROE and SUE are reported in percentage points. The portfolio formation period is from January 1996 through September 2008.

Panel A: Portfolios Double-sorted on IVOL and O/S

	Low O/S		Medium O/S		High O/S	
IVOL Decile	ROE	SUE	ROE	SUE	ROE	SUE
D1 (L)	4.09	-2.56	4.71	-1.41	4.84	2.19
D2	3.55	-3.41	4.87	-2.76	6.41	0.13
D3	2.93	-5.93	3.71	-3.7	4.16	-1.99
D4	2.71	-2.02	2.68	-3.65	2.53	-5.35
D5	2.05	-2.81	-1.40	-3.73	1.23	-3.24
D6	3.29	-4.00	-5.39	-6.84	-1.19	-5.40
D7	1.40	-5.85	-2.83	-6.34	-3.01	-6.83
D8	-8.88	-6.58	-8.24	-9.79	-7.69	-11.35
D9	-1.70	-9.92	-6.44	-11.25	-11.83	-11.67
D10 (H)	-5.79	-15.97	-11.51	-17.48	-10.84	-22.78
D1-D10	9.88	13.41	16.22	16.08	15.68	24.96
	(3.52)	(6.67)	(3.65)	(7.45)	(9.20)	(10.33)

Panel B: Portfolios Double-sorted on IVOL and OI/S						
	Low OI/S		Medium OI/S		High OI/S	
IVOL Decile	ROE	SUE	ROE	SUE	ROE	SUE
D1 (L)	3.85	-3.02	4.55	-2.25	5.23	3.47
D2	3.48	-4.75	5.88	-2.72	5.55	1.95
D3	3.22	-6.41	3.70	-3.6	3.79	-1.65
D4	2.83	-1.96	3.17	-2.64	1.99	-6.09
D5	-5.96	-1.82	-10.64	-3.88	1.11	-3.90
D6	3.01	-2.96	-13.89	-6.02	-9.70	-6.93
D7	1.86	-5.00	2.88	-6.92	-0.49	-7.19
D8	-16.47	-6.84	-12.23	-9.32	-13.28	-11.93
D9	-3.65	-8.95	-3.92	-11.47	-13.87	-12.36
D10 (H)	-8.49	-15.03	-8.13	-20.42	-11.94	-21.26
D1-D10	12.34	12.00	12.68	18.16	17.17	24.73
	(2.57)	(5.72)	(5.80)	(8.75)	(9.11)	(10.67)

Table X
Transaction Costs and Profitability of Synthetic Stock Strategies

This table reports estimates of option trading costs and net profits of option-based synthetic trading strategies after trading cost. Panel A reports the average percentage quoted spreads for the calls and puts used in calculating synthetic stock returns for our sample, separately for at the beginning and at the end of the portfolio holding month. The percentage quoted spread is the option quoted spread divided by the underlying stock price. Panel B reports the synthetic stock returns net of trading cost for the decile portfolios sorted by IVOL within the option trading subsample. The trading cost considered is the percentage effective spread, assumed to be a proportion of the percentage quoted spreads. The holding period for portfolios in this panel is one month. Panel C reports the synthetic stock returns net of trading cost for the decile portfolios sorted by IVOL within the option trading subsample, but the portfolios are held until option expiration during the second month after initial portfolio formation. t-statistics are reported in parenthesis. The portfolio formation period is from January 1996 through September 2008.

Panel A: Percentage Quoted Spreads for Options at the Beginning and End of Holding Month

	beginning of month						end of month					
	Call			Put			Call			Put		
IVOL Decile	1996-2008	1996-2003	2004-2008	1996-2008	1996-2003	2004-2008	1996-2008	1996-2003	2004-2008	1996-2008	1996-2003	2004-2008
D1(L)	0.36	0.40	0.29	0.35	0.38	0.29	0.34	0.37	0.27	0.33	0.36	0.27
D2	0.41	0.44	0.35	0.41	0.44	0.34	0.38	0.41	0.33	0.39	0.42	0.33
D3	0.46	0.49	0.39	0.46	0.5	0.38	0.44	0.47	0.37	0.44	0.47	0.37
D4	0.51	0.56	0.43	0.50	0.55	0.42	0.47	0.51	0.40	0.49	0.53	0.42
D5	0.59	0.64	0.50	0.59	0.65	0.49	0.54	0.58	0.46	0.59	0.65	0.48
D6	0.64	0.70	0.53	0.64	0.70	0.52	0.58	0.63	0.48	0.62	0.68	0.50
D7	0.73	0.79	0.61	0.73	0.81	0.60	0.66	0.72	0.55	0.74	0.81	0.60
D8	0.82	0.88	0.71	0.83	0.90	0.7	0.73	0.79	0.62	0.83	0.92	0.67
D9	0.94	1.02	0.79	0.95	1.03	0.81	0.83	0.90	0.72	0.98	1.08	0.79
D10(H)	1.19	1.25	1.07	1.22	1.28	1.09	1.02	1.09	0.90	1.25	1.35	1.06

IVOL	Return before	Effective Spread/Quoted Spread			
Decile	trading cost	0.25	0.50	0.75	1.00
Panel B: Synthetic Returns After Trading Cost – One Month Holding Period					
D1(L)	0.95	0.78	0.61	0.44	0.27
D2	0.96	0.76	0.56	0.37	0.17
D3	1.09	0.87	0.64	0.42	0.19
D4	0.96	0.71	0.47	0.22	-0.03
D5	0.76	0.47	0.18	-0.1	-0.39
D6	1.08	0.77	0.46	0.15	-0.16
D7	0.64	0.28	-0.08	-0.43	-0.79
D8	0.79	0.39	-0.01	-0.42	-0.82
D9	0.28	-0.18	-0.65	-1.11	-1.57
D10(H)	-0.73	-1.31	-1.90	-2.48	-3.07
D1-D10	1.68	0.93	0.17	-0.58	-1.34
	(2.05)	(1.13)	(0.21)	(-0.72)	(-1.64)
Panel C: Synthetic Returns After Trading Cost – Holding Until Expiration					
D1 (L)	1.72	1.63	1.54	1.45	1.36
D2	1.55	1.45	1.35	1.25	1.15
D3	1.85	1.73	1.62	1.50	1.39
D4	1.81	1.68	1.55	1.43	1.30
D5	1.45	1.30	1.15	1.01	0.86
D6	1.73	1.57	1.41	1.25	1.09
D7	1.54	1.36	1.18	1.01	0.81
D8	1.62	1.42	1.21	1.00	0.80
D9	0.73	0.50	0.26	0.02	-0.21
D10 (H)	-0.38	-0.69	-0.99	-1.29	-1.59
D1-D10	2.10	1.71	1.33	0.94	0.55
	(2.07)	(1.69)	(1.31)	(0.92)	(0.54)