Option Trading: Information or Differences of Opinion?

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Abstract

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Keywords: *option trading, differences of opinion, informed trading, speculation, earnings announcements.*

JEL classification: G10, G12 and G14.

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Abstract

This paper investigates the motive of option trading. We show that option trading is mostly driven by differences of opinion. Our findings are different from the current literature that attempts to attribute option trading to information asymmetry. We present three specific findings. First, cross-section and time-series regressions reveal that option trading is significantly explained by differences of opinion. While informed trading is present in stocks, it is not detected in options. Second, option trading around earnings announcements is speculative in nature and mostly dominated by small, retail investors. Third, around earnings announcements, the pre-announcement abnormal turnovers of options seem to predict the post-announcement abnormal returns. However, once we control for the pre-announcement returns, the predictability completely disappears.

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1. Introduction

Option trading has been steadily increasing. According to CBOE, in 2007, a total of 4.7 million transactions were made on options, representing a total dollar volume of $609 billion. These numbers more than doubled their counterparts a decade ago. If the market is complete, the trading volume of options should be indeterminate since one can create an equivalent option position by trading the underlying stock and a risk-free bond. Why the increase in trading volume then? An obvious answer is the presence of transaction costs which prohibits the perfect replication of options. Another potential reason is the leverage advantage identified by Black (1975). He argued that the leverage in options can attract informed traders attempting to exploit their private information. This line of thinking has motivated theoretical modelling and empirical testing of informed trading in options. Although supporting evidence is found in some studies (e.g., Amin and Lee, 1997; Easley, O'Hara and Srinivas, 1998; Cao, Chen and Griffin, 2005; and Pan and Potehsman, 2006), evidence to the contrary also exists (e.g., Stephan and Whaley, 1990; Vijh, 1990; Chan, Chung and Johnson,1993; and Chan, Chung and Fong, 2002). The overall empirical results on informed option trading are mixed at best. The main driving force of option trading has yet to be identified.

We take up this challenge in the current paper. We argue and empirically demonstrate that opinion dispersion is the main driver for option trading.[1] We arrive at our conclusion based on three pieces of empirical evidence. First, using data from OptionMetrics for the period of January 1, 1996 to December 31, 2006, we regress option turnovers on various proxies for information asymmetry and differences of opinion. Both the cross-section and time-series regressions reveal that option trading is significantly explained by opinion dispersion. While informed trading is present in stocks as is speculative trading, informed trading is largely absent in options. Second, the trading patterns around earnings announcements further confirm the presence of speculative trading and the absence of informed trading in options. Option trading increases significantly around earnings

[1] In this article, we use interchangeably the terms "differences of opinion", "opinion dispersion" and "disagreement." We also use the term "speculation" when called for. Different opinions could arise due to differential interpretations of public information (e.g., Kandel and Pearson, 1995) while speculation doesn't have to originate from information. Regardless, all the aforementioned terms are meant to be antonyms of "information" in our context, which in turn refers to private information.

announcements and the increase is almost entirely attributable to smaller, retail investors engaging in speculative trades. Third, around earnings announcements, the pre-announcement abnormal turnovers of options seem to predict the post-announcement abnormal returns. However, once we control for the pre-announcement returns, the predictive power of the pre-announcement turnovers completely disappears. Thus, option trading does not seem to contain information around earnings announcements; it is mainly driven by differences of opinion.

In establishing the broader evidence on the motive of trading, we use various proxies in the cross-section and time-series regression analyses. Following the literature, we use firm size, PIN and bid-ask spreads to approximate information asymmetry and use the earnings forecast dispersion and stock return volatility to capture the differences of opinion. We add two more proxies for opinion dispersion not previously used for this purpose in the literature. One is the number of analysts following the firm. The previous literature (e.g., Chae, 2005) has used it as an information proxy. However, Chordia, Huh and Subrahmanyam (2007) found that analyst coverage doesn't lead to a higher stock turnover, but that analysts are attracted to stocks with a higher turnover. Insofar as more analysts tend to produce more diverse opinions, it is logical to use the number of analysts as a proxy for opinion dispersion. The dispersion of earnings forecast doesn't subsume analyst coverage since the former is single-dimensioned (i.e., earnings per se) while the latter is multi-dimensioned (analyses / opinions of the firm aside from the forecasted earnings). The other new proxy for differences of opinion is "market sidedness" introduced by Sarkar and Schwartz (2009). It is essentially the correlation between the numbers of buyer- and sell-initiated trades during the day. If buyer- and seller-initiated trades tend to occur simultaneously, sidedness will be high, indicating more diverse opinions.

Broadly speaking, the literature related to our study can be classified into two categories: 1) theories and empirical studies explaining what drives the trading of stocks and 2) theories and empirical studies investigating either the informational lead-lag relationship between the stock and the option markets or simply the informational role of option trading.

Faced with the "no-trade theorem" of Milgrom and Stokey (1982) yet the large trading volume in stocks, researchers have come up with various explanations for trading. Building on the concept of noisy rational expectations (Hellwig, 1980; and Diamond and Verrecchia, 1981), researchers (e.g., Gloston and Milgrom, 1985; Kyle, 1985; and Easley, Kiefer, O'Hara and Paperman, 1996) came up with models consisting of exogenous liquidity traders and informed traders attempting to exploit their informational advantage. Subsequent efforts (e.g., Admati and Pfleiderer, 1988) were made to allow the liquidity traders to be strategic. This line of reasoning seems to have some empirical support (e.g., Chae, 2005).

Realizing the limitation of purely information-based trading theories, subsequent researchers introduced differential interpretations of public information (e.g., Varian, 1989; Harris and Raviv, 1993; Kim and Verrecchia, 1994; and Kandel and Pearson, 1995). In these models, agents use different likelihood functions to update their beliefs upon receiving new information, resulting in different opinions or disagreement on public information, hence trades ensue. These opinion-dispersion models have enjoyed much empirical support. Kandel and Pearson (1995) offered evidence of extensive trading around earnings announcements due to differential opinions. Numerous other authors were also able to explain trading in various contexts based on opinion dispersion (e.g., Bessembinder, Chan and Seguin, 1996; Bamber, Barron and Stober, 1999; Diether, Malloy and Scherbina, 2002; Hong and Stein, 2006; Chordia, Huh and Subrahmanyam, 2007; and Sarkar and Schwartz, 2009). The empirical evidence for the stock market in its entirety seems to suggest that there is both informed trading and trading based on differences of opinion.

The second strand of literature is still in its early stage and the overall empirical evidence is mixed concerning the lead-lag relationship between the stock and the option markets or the informational role of options. Building on the insight that options offer a leverage advantage over stocks (Black, 1975), Easley, O'Hara and Srinivas (1998) developed an asymmetric information model in which informed traders may trade in both the stock and the options markets. Subsequent efforts were made to verify information trading in the options market and / or the price discovery role of options and these efforts were met with some success (e.g., Amin and Lee, 1997; Chakravarty, Gulen and Mayhew, 2004; Cao, Chen and Griffin, 2005; Pan and Poteshman, 2006; and Roll, Schwartz and Subrahmanyam, 2008). However, equally convincing evidence was also presented by other authors who showed that 1) informed trading doesn't exist in options (Vijh, 1990), 2) the option volume does not lead stock prices (Chan, Chung and Johnson, 1993; and Chan, Chung and Fong, 2002), and 3) the stock market leads the option market (Stephan and Whaley, 1990).

Unlike the aforementioned studies in the two strands of literature, Roll, Schwartz and Subrahmanyam (2009) explored an interesting angle by examining the trading activities of options relative to those of the underlying stocks. They found that the trading ratio is related in cross-section to variables such as firm size and implied volatility. The trading ratio is higher around earnings announcements and its relation to returns seems to suggest that some portion of the option trading may predict future returns. They then concluded that options trading can improve market efficiency. Their focus is not on what drives option trading per se.

If information is not the driving force for option trading, what are the possible drivers then? Hedging is an obvious candidate. However, unless all hedging is carried out dynamically, it is questionable if this type of demand would explain the large volume of trading. Besides, Lakonsihok, Lee, Pearson and Poteshman (2006) found that the most popular option-trading strategy is covered call writing, followed by purchasing calls and writing puts, none of which appears to be a logical hedge for the underlying. The discussions lead us to what we consider to be the most plausible motive of option trading: differences of opinion or opinion dispersion.

The literature on differences of opinion in the context of option trading is sparse. Buraschi and Jiltsov (2006), Buraschi, Trojani and Vedolin (2008), and Cao and Ou-Yang (2009) are a few exceptions. None of the three studies directly focuses on the question of whether opinion dispersion is the sole driving force for option trading. In other words, they all abstracted away from information asymmetry and could not shed light on the relative impacts of information and disagreement. Buraschi and Jiltsov (2006) focused on model uncertainty and pricing implications of heterogeneous beliefs. Buraschi, Trojani and Vedolin (2008) focused on the relation between heterogeneous beliefs and cross-section differences on option returns and showed that more diverse opinions lead to a higher risk premium for the volatility risk. Cao and Ou-Yang (2009) developed a theoretical model of trading for both stocks and options based on differences of opinion. They showed that option trading should concentrate around periods of heightened disagreements whereas trading in stocks may be diffuse.

We empirically confirm that opinion dispersion is the main driving force for option trading, especially around earnings announcements. More importantly, we find no evidence of information trading in options.

The contribution of this paper is three-fold. First, our study represents the first endeavour to empirically verify the importance of opinion dispersion for option trading implied from the theoretical models (e.g., Cao and Ou-Yang, 2009). Second, to the best of our knowledge, this is the first paper attempting to establish empirically the relative roles of information asymmetry and differences of opinion in option trading. We convincingly show that differences of opinion are the main driving force. Third, we offer some insights as to why certain studies have found apparent informed trading in options. We argue that investors use options to speculate on the current trend of stock price. Investors also take other cues from the stock market (such as the behavior of order imbalance) and trade in the option market accordingly. Option trading of such nature would appear *as if* the current period's option volume predicts next period's stock returns.

The rest of the paper is organized as follows. Section 2 describes the data and defines the main variables used in the regressions. Section 3 presents the main results of the paper. It is divided into four subsections. In the first subsection, we present the broad evidence of opinion-based trading in options through cross-section and time-series analyses. In the second subsection, we examine the trading patterns around earnings announcements and show that the surge in volume is mostly due to small investors engaging in speculative trading. A refined test is offered in the third subsection, proving unambiguously that the apparent predictability of option turnovers for future returns is simply spurious. The last subsection offers some reconciliation with the existing literature and explains why our findings are different. Section 4 concludes the paper. Tables, figures and the appendix are relegated to the end.

2. Data description and variable definitions

The primary source of option data is Ivy DB's OptionMetrics for the period of January 1, 1996 to December 31, 2006. Among other things, the database provides the day-end best bid and ask quotes, open interest and volume for all exchange-traded options on U.S. stocks.[2] For the same sample period, the trading volume, daily return, closing price and the number of shares outstanding for the underlying stocks are obtained from CRSP. The intraday quote and transaction data for stocks are retrieved from TAQ. Quarterly earnings forecasts and announcements come from I/B/E/S. Finally, the open/close summary data for the period of January 1, 2006 to July 31, 2006 are obtained from CBOE. This dataset breaks down the total daily trading volume for each option along three dimensions: initiator (firm/customers), trade type (buy/sell/open/close), and trade size (small/medium/large). Here, "firm" refers to proprietary trading by brokerage firms on their own account while "customers" are traders other than firms and the market markers; "open/close" refers to whether the transaction is for opening or closing a position; and the size classification only applies to trades by customers as follows (in terms of number of contracts): small < 100, $100 \leq$ medium ≤ 199, and large ≥ 200. As a result, for each call or put option, there are 16 possible combinations.

Aside from volume, we use two additional measures to characterize trading. The first is turnover. For stocks, this is the daily trading volume divided by the number of shares outstanding; for options, it is the volume divided by open interest. We take logarithm of the turnovers to achieve close-to-normal distributions (please see the appendix for details). The second measure is the "*scaled-ratio*", which is essentially the relative volume of options with respect to the stock's (again, please see the appendix for details).

Information asymmetry and differences of opinion are each measured with four proxies. For information asymmetry, the proxies are firm size (Atiase, 1985), PIN (Easley, O'Hara and Paperman,

[2] From November 28, 2000 and onward, OptionMetrics recorded the open interest by a one-day lag for all options. We adjust for the lag in our study. Moreover, we only include options whose underlying stocks are traded on NYSE/AMEX. We exclude options on Nasdaq stocks since the interdealer feature of Nasdaq could possibly bias some of our measures constructed from intraday data. Finally, we only keep options satisfying the following conditions: 1) maturity is between seven and 60 calendar days, 2) (stock price)/(strike price) in the range of (0.9, 1.1), and 3) bid quote is bigger than one tick. In the resulting sample, the number of firms ranges from 802 in 1996 to 1,695 in 2006.

1996), stock spread and option spread (Copeland and Galai, 1983; and Glosten and Milgrom,1985); for differences of opinion, the proxies are stock return volatility (Shalen, 1993), dispersion of earnings forecasts (Diether, Malloy and Scherbina, 2002), sidedness (Sarkar and Schwartz, 2009) and the number of analysts following the firm.

Small firms, higher PIN and wider spreads are expected to be associated with more severe information asymmetry. Firm size is simply the daily closing price times the number of shares outstanding. Quarterly PIN is obtained from Stephen Brown's web-page. Option spread is the proportional bid-ask spread calculated as the dollar spread divided by the mid-point of the bid and ask quotes. The proportional bid-ask spreads for all contracts are averaged to arrive at a daily proportional spread. The stock spread is also defined as the proportional bid-ask spread and is computed using data from TAQ. Specifically, to roughly match the timing of the option quote at the end of the trading day, we first average, respectively, the bid and ask quotes in the five minutes prior to the last trade of the day; we then calculate the proportional bid-ask spread as the difference between the average ask and average bid, divided by the mid-point.

As for the differences of opinion, the first proxy is the stock return volatility, which is calculated as the square of returns. A higher volatility reflects a wider range of prices which in turn indicates a greater extent of disagreement among investors. The second proxy is the dispersion of earnings forecasts, denoted as $DISP$. A higher $DISP$ reflects diverse opinions among analysts which can stir even more diverse opinions among investors. In light of the monthly reporting frequency by I/B/E/S and the known biases in earnings estimates (Diether, Mally, and Scherbina, 2002), we use the Unadjusted Summary file to compute the forecast dispersion on our own. Specifically, for each day, $DISP$ is calculated as the standard deviation of earnings per share forecasted for the coming fiscal quarter. We also define a variant of the forecast dispersion, denoted by $Scaled\_DISP$ which is $DISP$ scaled by the average stock price within the calendar year of the estimates. In total, there are 21,185 quarterly earnings announcements.

The third proxy is the "sidedness" measure developed by Sarkar and Schwartz (2009). To our knowledge, aside from the original authors, we are the first to use this variable as an explicit proxy for dispersion of opinion. Simply put, "sidedness" measures whether the trading during a day is one-sided or two-sided. If the buyer-initiated trades are mostly matched with seller-initiated trades, then it is a two-sided market and most likely driven by differences of opinion; otherwise, it is likely to be driven by asymmetric information. To estimate the degree of opinion dispersion for a particular stock on a given day, we first partition the trading day into five-minute intervals and aggregate the number of buyer- and seller-initiated trades within each interval. We then calculate the sidedness as the correlation between the numbers of trades initiated by buyers and sellers.[3]

The last proxy for differences of opinion is the number of analysts, which is calculated as the logarithm of one plus the actual number of analysts. It should be noted that previous researchers have used this variable to proxy information asymmetry (e.g., Chae, 2005; and Chordia, Huh and Subrahmanyam, 2007). As shown in Hong, Lim and Stein (2000), a wider analyst coverage will facilitate more information production and hence reduce information asymmetry. However, Chordia, Huh and Subrahmanyam (2007) established that analysts following doesn't cause more trading; instead, analysts seem to chase stocks that have higher turnovers. Easley, O'Hara and Paperman (1998) also argued that analysts actually facilitate the production of public information as oppose to originating private information. If we take it that analysts disseminate public information and more information potentially leads to a wider divergence of opinions, then the number of analysts would be a good proxy for differences of opinion. It is worth noting that even if the dispersion in earnings forecasts is small, more analysts can still lead to a wider divergence of opinions since investors also read the analyst reports. Analysts may arrive at similar forecasts via quite different routes which sow the seeds for different opinions.

Several additional notes are in order with respect to the construction of data and regression variables. First, following Chordia, Huh and Subrahmanyam (2007), we use as control variables

[3]Note that a more two-sided market does not necessarily mean a lower order imbalance, because the sidedness measure abstracts from the size of buyer- and seller-initiated trades. Sarkar and Schwartz (2009) showed that the two measures are informative of each other, but opinion dispersion is only reflected in sidedness, not order imbalance. We avoid using order imbalance to proxy information asymmetry or differences of opinion precisely because of its ambiguity. For instance, when we defined order imbalance based on volumes, on a non-information day, the numbers of buyer- and seller-initiated trades would be quite close, but the order imbalance could be large if one of the trades is sizeable (say, from an institutional investor trading for liquidity reasons). Nevertheless, we will make use of order imbalance in the last part of our study for a different purpose.

the stock price and returns while regressing turnovers on various proxies of information asymmetry and differences of opinion.

Second, aside from turnovers and the number of analysts, we also take logarithm of the stock price and firm size.

Third, to balance between reducing the noise in daily data and having a large enough number of observations, we follow Lo and Wang (2000) and aggregate the data into weekly frequency. Specifically, we obtain weekly observations by averaging daily observations within a calendar week.

Fourth, to combat potential nonstationarity, we detrend all variables (other than stock returns) used in the regression analyses. The detrending is done following the procedure in Gallant, Rossi and Tauchen (1992) as did in Chordia, Huh and Subrahmanyam (2007). This procedure ensures that the adjusted series retains the same mean and variance as the original series to facilitate the interpretation of empirical results. Note that the sudden drop / jump in the stock price due to stock split / reverse split can create a spurious trend in the price series. To get around this, we detrend the logarithm of the adjusted price and recover the unadjusted price afterwards. For the logarithm of one plus the number of analysts, we add "announcement-week" and "after-announcement-week" dummies in the detrending procedure. The additional dummy variables are necessary since most analysts don't post their estimates for the following quarter immediately after the earnings announcement for the current quarter. The seemingly lower number of reported forecasts right after each announcement is not a reflection of fewer analysts following the stock. The appendix summarizes all the variables used in the regression analyses in the early part of the paper.

Table 1 contains the summary statistics for the main variables used in the regressions. The pooled (across stocks and weeks) mean, median, standard deviation, minimum and maximum for each variable prior to detrending are reported at the bottom of the table. The upper portion of the table reports the weekly average and the corresponding t-value of correlations among the detrended variables. Several variables are highly correlated with *Alog_size*: *Alog_price*, $APIN$, *Astockpba*, *Aoption_pba*, *Alog_num_analyst*, *and Asidedness*. The signs of these correlations are intuitive. To minimize the impact of multicollinearity in the cross-section analysis, we will avoid putting highly correlated variables in the same regression.

3. The drivers of option trading: empirical evidence

We employ two strategies to study the nature of option trading. In the first instance, we run cross-section and time-series regressions to see how information asymmetry and differences of opinion affect trading; in the second, we infer the impact of the two potential drivers by closely examining the trading activities around earnings announcements. When warranted, we compare the trading dynamics of the option market with the underlying stock market.

Based on the strategies, we divide the empirical section into four subsections. In the first subsection, we run both cross-section and time-series regressions to investigate how trading is affected by information asymmetry and differences of opinion. We show that firms with a wider dispersion of opinion enjoy more active trading in both stocks and options. Information asymmetry seems to have an impact on the turnover of stocks, but not on options. In the second subsection, we narrow the investigation to the trading behavior around earnings announcements. We contrast the trading patterns of stocks and options and reinforce the conclusion that, while stocks' trading is subject to information asymmetry, option trading is mostly driven by speculative motives. We use data on broken-down option volumes to demonstrate that the surge of option trading around earnings announcements is primarily driven by small, speculative investors. In the third subsection, we continue the investigation around earnings announcements and ascertain whether pre-announcement trading volumes contain any information on post-announcement stock returns. We find that the stocks turnover does predict future returns, but the options turnover doesn't. Finally, in the last subsection, we reconcile our findings with the existing literature.

3.1. Broader evidence on opinion-based trading in options

3.1.1. Cross-section analysis

Chordia, Huh and Subrahmanyam (2007), among others, investigated the general property of stock trading activities using various explanatory variables. Most of the existing literature on option trading focused on specific events (e.g., Amin and Lee, 1997; and Cao, Chen and Griffin, 2005). Roll, Schwartz and Subrahmanyam (2009) is one exception, but they examined the ratio of option trading over stock trading. In this subsection, we attempt to obtain some general insights into option trading. We start with cross-section regressions. Specifically, in reference to Chordia, Huh and Subrahmanyam (2007) and according to our own focus, we run the following predictive cross-section regression for stocks:

$$\begin{aligned} Alog\_stock\_turnover_t = (&Alog\_size, APIN, Astock\_pba, Alog\_num\_analyst, Asidedness, \\ &ADISP, Avolatility, Alog\_price, Return\_positive, Return\_negative)_{t-1}, \end{aligned} \tag{3.1}$$

where the parentheses collect all the independent variables aside from the intercept, the subscripts t and $t-1$ signify the predictive nature of the regression, and *Alog_price*, *Return_positive*, and *Return_negative* are control variables. As in Chordia, Huh and Subrahmanyam (2007), stock price is used to control for visibility, and stock returns are included to capture effects of portfolio rebalancing demands. *Return_positive* is the return of the week if it is positive and zero otherwise, and *Return_negative* is defined analogously. The regression for stocks is only used as a backdrop. Our main focus is on option trading. To this end, we run a similar cross-section regression for options with two modifications: 1) add the options proportional spread (*Aoption_pba*) as an independent variable, and 2) remove the two return variables since it is unlikely that options are held for long-term investment purposes. Specifically, the regression is as follows:

$$\begin{aligned} Alog\_option\_turnover_t = (&Alog\_size, APIN, Astock\_pba, Aoption\_pba, \\ &Alog\_num\_analyst, Asidedness, ADISP, Avolatility, Alog\_price)_{t-1}, \end{aligned} \tag{3.2}$$

where *Alog_option_turnover* and *Aoption_pba* could be for calls and puts separately or for all options combined, depending on the version of regression we run. The cross-section regressions are run weekly and the coefficient estimates are averaged across time. The corresponding t-values are adjusted for potential autocorrelation following the Newey-West procedure. For completeness, we also run a univariate regression for each independent variable. Table 2 reports the results.

While we briefly explained in the previous section the rationales of the main proxies, some further discussions are in order before we interpret the regression results. To begin, we need to establish our priors regarding the impact of various proxies on the turnover. The priors on the proxies for differences of opinion are relatively straightforward: More disagreements lead to more trading. We therefore anticipate a positive sign for $Alog\_num\_analyst$, $Asidedness$, $ADISP$ and $Avolatility$ in both (3.1) and (3.2).

As for information asymmetry, we need to first understand the time-series trading properties for a single stock in the presence of information. As shown by Chae (2005) and others, the turnover of stocks tends to go down before scheduled information events such as earnings announcements and go up before unscheduled events such as M&A announcements. The opposite reactions are mainly due to the behavior of discretionary liquidity traders. They postpone transactions before scheduled public announcements in order to avoid trading with informed traders, causing the turnover to go down; for unscheduled events, by definition, the discretionary liquidity traders have no knowledge of them and unwittingly become the counterparts of the informed traders, causing the turnover to go up. As a result, we are less likely to detect cross-section differences in trading due to public information events since they tend to affect all stocks at the same time and in similar ways. For instance, macro-economic news will have simultaneous impacts on all stocks; the fiscal year of most firms coincides with the calendar year and as a result the earnings announcements tend to come out at the same time; and so on. Thus the cross-sectional differences in trading, if any, are most likely caused by unscheduled events. We can reasonably argue that the more severe the information asymmetry, the bigger its impact on trading. Putting all the above together, we anticipate that small firms, higher PIN's and wider bid-ask spreads are associated with more trading cross-sectionally. Therefore we expect a negative sign for $Alog\_size$ and a positive sign for $APIN$, $Astock\_pba$, and $Aoption\_pba$.

Panel A of Table 2 contains the regression results for stocks. First and foremost, all four proxies of differences of opinion have a positive coefficient in all versions of the regressions and are significant at the 1% level. Opinion dispersion unambiguously increases trading. As for trading due to information asymmetry, only the size variable shows the strongest support with a significant negative coefficient. The PIN variable has the right sign and the t-values are significant at the 1% level, though much smaller than those for the size variable. The spread variable is only marginally positive in the multivariate regression. Taken together, the results demonstrate convincingly the strong, positive impact of opinion dispersion on turnovers, and the mild impact of information asymmetry.

Incidentally, it is apparent from the R-squares of the univariate regressions that the variable "sidedness" proves to be a successful proxy for dispersion. It commands the highest explanatory power among all the variables save firm size.[4]

We now turn to options in Panel B of Table 2.[5] To the extent that options are more advantageous than stocks due to their leverage (Black, 1975), we should see stronger effects of information asymmetry and opinion dispersion on turnovers. Indeed, the R-squares and t-values are generally higher in Panel B than in Panel A. Once again, the coefficients for all four proxies of opinion dispersion are positive and significant at the 1% level in all versions of the regressions, confirming the impact of opinion dispersion on trading. However, the coefficients for $Alog\_size$, $APIN$, $Astock\_pba$ and $Aoption\_pba$ strongly contradict the hypothesized impact of information asymmetry on trading. They are all highly significant, but with the wrong sign. We see from the univariate regressions that, the firm size and option spread ($Alog\_size$ and $Aoption\_pba$) have the highest explanatory power. It becomes clear that they simply capture the liquidity effect on trading: Bigger firms and options with narrower spreads are traded more actively. The PIN variable ($APIN$) and the stock's spread ($Astock\_pba$) are just the other side of the same coin: Stocks of larger firms tend to have a narrower spread and a lower probability of informed trading. What transpires from the results is: Aside from liquidity, differences of opinion appear to be the main driving factor for option trading.

That informed trading is carried out in the stock market but not in the option market is rather intriguing, given the leverage advantage of options. Although our current focus is not on why informed trading is not carried out in the option market, we would conjecture that one simple reason is the limited size of the option market and its low liquidity.

[4]Note that, while the two control variables on returns have the same signs as in Chordia, Huh and Subrahmanyam (2007), the coefficients for size and price are both negative, in contrast to the positive sign in Chordia, Huh and Subrahmanyam (2007). The main reason is our sample's concentration on larger stocks (since they are optioned stocks). In fact, as shown in Chordia, Roll and Subrahmanyam (2008, Table 7), larger firms are indeed associated with lower turnovers. We will investigate this finding further in a separate study.

[5]The results are for call and put options combined. Those for calls and puts separately are similar and are omitted for brevity.

3.1.2. Time-series analysis

Having learnt about how various characteristics affect trading across stocks, we now study how the trading of a particular stock and its options is affected by the evolution of information asymmetry and differences of opinion. Again, to avoid potential endogeneity, we run predictive time-series regressions as follows:

$$\begin{aligned} Alog\_stock\_turnover_t = (&Alog\_size, APIN, Astock\_pba, Alog\_num\_analyst, Asidedness, \\ &Ascaled\_DISP, |Ascaled\ change\_DISP|, Avolatility, Alog\_price, \\ &Return\_positive, Return\_negative, yearly\_dummies)_{t-1}, \end{aligned} \tag{3.3}$$

$$\begin{aligned} Alog\_option\_turnover_t = (&Alog\_size, APIN, Astock\_pba, Aoption\_pba, Alog\_num\_analyst, \\ &Asidedness, Ascaled\_DISP, |Ascaled\ change\_DISP|, Avolatility, \\ &Alog\_price, yearly\_dummies)_{t-1}, \end{aligned} \tag{3.4}$$

where $Ascaled\_DISP$ and $|Ascaled\ change\_DISP|$ are the level and absolute change in the dispersion of earnings forecasts scaled by the average stock price within the calendar year. The scaling is to facilitate the aggregation of regression coefficients across stocks. The time-series regressions are run for individual stocks and the coefficients are averaged across stocks using the reciprocals of standard error as weights. To be included in the regression, a firm must have at least one-year's worth of data (i.e., 52 weekly observations). Univariate regressions and one multivariate regression are run for (3.3) and (3.4). The multivariate regression doesn't exclude any explanatory variables since the time-series correlations among the variables are low compared with those in Table 1. Table 3 reports the results.

Some discussions on the priors are in order before interpreting the results. An increase in disagreements should lead to more trading in the next period. Therefore, we expect a positive sign for all the proxies of opinion dispersion: $Alog\_num\_analyst$, $Asidedness$, $Ascaled\_DISP$, $|Ascaled\ change\_DISP|$ and $Avolatility$. Notice that we hypothesize a positive impact of the absolute change in the dispersion of earnings forecasts. When the forecast dispersion widens, the optimists / pessimists will increase their long / short positions, leading to more trading; when the forecast dispersion narrows, both the optimists and pessimists will reduce their holdings, again leading to more trading.

The sign of the proxies for information asymmetry is not clear-cut *a priori*. As alluded to earlier, on one hand, before scheduled public information releases, more severe information asymmetry would predict less trading due to the withdrawal of discretionary liquidity traders; on the other hand, before unscheduled information events, more severe information asymmetry may lead to more trading since discretionary liquidity traders could not tell apart the informed traders and thus they will simply trade along. Insofar as there are more scheduled information releases than unscheduled, it is reasonable to anticipate that the former would dominate the time-series dynamics of trading. We should expect to see a negative impact of information asymmetry on trading. In other words, we expect the sign to be negative for both the PIN variable ($APIN$) and the spread variables (*Astock_pba* and *Aoption_pba*).

Panel A of Table 3 reports the results for stocks. Similar to the cross-section regressions, the proxies of opinion dispersion all have significant, positive coefficients, confirming the role of differences of opinion in trading. The dispersion of earnings forecasts is significant in the univariate regression, but insignificant in the multivariate regressions. However, its change is significant in both cases, confirming our conjecture. As for information asymmetry, the PIN variable is not significant, perhaps due to the poor testing power resulting from its quarterly frequency. The coefficient for the spread variable is positive and significant, contrary to our priors. One potential reason is perhaps the crude time period (i.e., a week) used in the regressions. To verify this, we repeated the regression using daily observations and did obtain a negative and significant coefficient for the spread variable. Regardless, the impact of differences of opinion on trading is strong and clear-cut while that for information asymmetry is ambiguous at best.

We now turn to the option results in Panel B of Table 3. Similar to stocks, the option turnover is strongly affected by the differences of opinion. Except for the level of forecast dispersion, all other proxies have a positive coefficient that is significant at the 1% level. The PIN variable is insignificant, but both spread variables (*Astock_pba* and *Aoption_pba*) have a highly significant, negative coefficient. Moreover, when the lagged explanatory variables are replaced by contemporaneous variables, the coefficients for *Astock_pba* and *Aoption_pba* remain negative and highly significant. Whatever explains the reversal of sign for *Astock_pba* in the case of stock would be inconsistent with the results for options. In other words, instead of confirming the role of information asymmetry in option trading, the negative sign of *Astock_pba* and *Aoption_pba* may simply capture the liquidity effect as demonstrated in the cross-section results. All said, our time-series analyses strongly support the notion that a wider opinion dispersion would lead to more trading in options whereas it is not clear at all if information asymmetry would have any impact.

3.1.3. Option trading volume relative to stock trading volume

We have shown that the turnovers of both stocks and options are driven by disagreement. We now investigate which market is more susceptible to opinion dispersion. If options are used primarily for speculation or exploiting beliefs, then we should expect to see a higher sensitivity from the option market. To this end, we introduce the variable *Alog_scaled_ratio*, similar to but different from the option-stock trading ratio defined in Roll, Schwartz and Subrahmanyam (2009). As seen in the appendix, it is essentially the option volume relative to the total volume of stock and options. To adjust for the fact that the option volume is usually much lower than the stock's, we use the ratio of the sample means to scale up the option volume. This procedure ensures that the proportion of option trading relative to total trading of options and the stock is evenly distributed in the range of [0, 1].

When the opinion dispersion widens, the trading volumes of both the stock and options tend to increase as established before. Now, if investors choose to trade more in the option market upon facing a wider disagreement, then *Alog_scaled_ratio* should increase. However, if investors choose to trade in the stock market when the opinions become more diverse, then *Alog_scaled_ratio* should decrease. To investigate how the relative volume of options responds to differences of opinion, we repeat the cross-section regression in (3.2) and the time-series regression in (3.4) by replacing the option turnover variable with *Alog_scaled_ratio*. The sign and significance of all the explanatory variables are very similar to those in the case of option turnovers. For brevity, we only report the results for the time-series regression in Table 4.

It is seen that the coefficients for four of the five opinion-dispersion proxies (*Alog_num_analyst*,

$Asidedness$, $|Ascaled\ change\_DISP|$ and $Avolatility$) are positive and their t-values are all significant at the 1% level. In the unreported results for the cross-section regressions, all coefficients for the opinion-dispersion variables are positive and highly significant. The results therefore imply the following: 1) for different stocks, those that are associated with more disagreements tend to have a higher volume of option trading relative to the stock, and 2) for the same stock across time, when the dispersion of opinion widens, investors trade more options relative to the underlying stock.

3.2. Trading patterns of options around earnings announcements

The analyses so far are not based on any specific information events. The regression results produce broad evidence on the importance of differences of opinion on option trading. From this point on, we anchor our analyses on a specific type of information event, namely, quarterly earnings announcements. We hope to sharpen our conclusion that disagreements as opposed to information are the main driving force for option trading. We first study the general trading patterns around earnings announcements; we then examine who contribute to the higher option turnover around earnings announcements.

3.2.1. Option trading controlling for price movements

The analyses here closely resemble that in Table 2 of Kandel and Pearson (1995) who studied stock trading around earnings announcements. Below, we briefly summarize the basic idea of Kandel and Pearson (1995). First, we ascertain if there is any abnormal trading around earnings announcements. If the stock turnover is not different from that of the non-event period, then we can rule out the effects of both information and opinion dispersion. Next, if we do observe abnormal trading around earnings announcements, then we need to sort out the separate impacts of information and opinion dispersion. Insofar as returns are the ultimate revelation of private information, we should not see cross-section differences in abnormal turnovers within the same return range. For instance, if the average returns for the non-event period and the announcement period are roughly equal, yet the turnovers are drastically different, then information cannot be the driver since we have already controlled for it via returns. The only remaining plausible driver would be speculation or differences of opinion. We extend this line of reasoning to options.

Following the methodology of Kandel and Pearson (1995), we define day 0 as the earnings reporting date and other periods as follows: [-42, -23] as the control period, [-22, -5] as the non-event period, [-4,-2] as the pre-announcement period, [-1, +1] as the announcement period, and [+2, +10] as the post-announcement period. Each period is then divided into 3-day segments and the segment-sum of stock returns and the segment-average of turnovers (in logarithm) are calculated. We subtract the control-period turnover from those of the other periods and call the resulting differences "abnormal turnovers". For each period, we divide the raw-return domain into 22 mutually exclusive ranges. We then match each return-range across different periods and tabulate the corresponding abnormal turnovers. Table 5 presents the results. For brevity, we only report the abnormal turnover for the non-event period. The rest are pair-wise differences in abnormal turnovers, all relative to the non-event period: (Pre − Non), (At − Non), and (Post − Non). The abbreviation "Non" stands for non-event period while "Pre", "At" and "Post" stand for pre-announcement, announcement and post-announcement periods, respectively.

For stocks, the results are consistent with those in Kandel and Pearson (1995) and Chae (2005): There is generally a drop in turnover during the pre-announcement period and a sharp increase in the announcement and post-announcement periods. This is consistent with the view that discretionary liquidity traders withdraw from trading before the announcement and come back right after. The fact that the abnormal turnover is significantly high for the announcement and post-announcement periods even when the price movement is near zero (referring to the middle cells in the table) means that the trading is most likely caused by investors' differential interpretations of the same information or opinion dispersion.

If there is also information trading in options in the pre-announcement period, we should see a similar dip in the turnover. The table shows quite the contrary: The option turnover actually shoots up in the pre-announcement period. Trading is the most active during the announcement period, but drops below the pre-announcement period level after the announcement. This is in sharp contrast with stocks whose post-announcement turnover is much higher than that of the pre-announcement period. To appreciate the magnitude of increase in the option turnover, take the return cell of [$-0.5\% \leq R < 0$] for call options as an example. The abnormal turnover for the pre-announcement and announcement periods are 0.439 and 1.327 respectively. Since the turnovers are in natural logarithms, the abnormal turnovers mean that the turnovers in the pre-announcement and announcement periods are 1.55 and 3.77 times that of the non-event period. In summary, the active trading of options starts well before the actual announcement, leading up to the climax during the announcement period and quickly dies off after the announcement, consistent with the patterns of opinion-based trading or speculation. Taken together, the results in Table 5 clearly demonstrate that, unlike stocks, options are used for speculation purposes around earnings announcements.

One potential, alternative explanation for the option trading pattern is the hedging demand for options due to the large movements in stock prices around earnings announcements. However, the stratification by returns is to control for the price movement in the underlying stock. One may argue that it is the anticipation of price movements that causes the additional hedging demand. But this essentially is one type of opinion dispersion or speculation.

Another alternative explanation is information trading itself. As pointed out by Kandel and Pearson (1995), the abnormally high turnover at and after the earnings announcement periods can still be consistent with information trading if the private information production is concentrated around the announcement and if all investors interpret the public signals identically (i.e., no differences of opinion). Kandel and Pearson (1995) did not resolve this issue for stocks and left it as an open possibility. However, we eliminate this possibility for options by resorting to two pieces of evidence. First, if the production of private information occurs around the earnings announcement, then according to the thesis of discretionary liquidity traders staying away from the market, we should also see a lower turnover for the announcement period, and a higher turnover sometime after the announcement or information production. The higher turnovers shown in Table 5 for both the announcement and post-announcement periods invalidate the hypothesis of private information production. Second, we will show that investors *do not* interpret the information identically around earnings announcements, since only small investors trade options heavily. This is the focus of the subsection below.

3.2.2. Are all option traders equally active around earnings announcements?

We utilize the open/close dataset from CBOE to address this question (the dataset is similar to, but less elaborate than the one used by Pan and Poteshman, 2006). As described in the data section, this dataset covers the period from January 1, 2006 to July 31, 2006 and contains daily breakdowns of option volumes by trade type (open/close/buy/sell), size (small/medium/large) and initiators (firm/customers). This dataset has several advantages. First, the breakdown according to trade initiation facilitates the differentiation between well informed traders (i.e., brokerage firms trading on their own accounts) and less informed traders (i.e., small, retail investors). Second, within the category of customers traders, the trade size can help distinguish small investors from large investors. Third, the open/close/buy/sell breakdown can help detect if investors are opening or closing their positions when buying or selling. The breakdowns create 16 distinct types of transactions.

Similar to the setup in Table 5, we set the control period as [-42, -23]. We then examine the trading activity for each of the 16 types of transactions around the earnings announcement. We specifically focus on the 21-day window: [-10, +10]. To see who are active in certain types of transactions, we examine the relative proportion of each type transaction's volume over the total volume. Specifically, we first calculate the average proportion of each type/size/initiator combination relative to the total volume in the control period, and then calculate the abnormal proportions for each day in the period [-10, +10] by subtracting the corresponding proportion in the control period. Figure 1 contains the plots for the abnormal proportions. Figures 1A and 1B are for calls while Figures 1C and 1D are for puts. Two striking patterns emerge.

First, small investors (with trade size less than 100 contracts) are the only active traders around earnings announcements. In fact, almost all other investors (traders with medium and large sizes or brokerage firms trading on their own accounts) curtail their trades in this period relative to the control period. Arguably, brokerage firms and large investors are the prime candidates of informed traders while small investors are speculators. In this sense, the plots show no indication of information trading but does show convincing evidence of speculation by small investors.

Second, the nature of transactions by small investors also confirms their speculative behavior. Take call options as an example. As shown in Figure 1A, 10 days prior to the announcement, small investors already become more active (relative to the control period) in initiating long positions by purchasing calls (the abnormal proportion is around 5%). They then steadily pick up the speed and dramatically increase their dominance in the total trading volume. By the day prior to the announcement, their proportion in purchases increases by about 20% relative to the control period. Within the same period, the proportion of sell-to-open (i.e., writing call options) transactions steadily decreases, indicating the one-way betting on good news. The purchase proportion drops precipitously after the announcement while the sell-to-open proportion is recovering back to normal. In fact, the closing of betting positions after the announcement is clear in Figure 1B. The sell-to-close abnormal proportion shoots up dramatically and stays high (around 8%) for quite some time. The buy-to-close abnormal proportion also goes up after the announcement, though at a much subdued speed. Figures 1C and 1D for puts depict a similar picture. While one may argue that the building-up of long positions before the announcement and the speedy liquidation afterwards are also consistent with the pattern of informed trading, it is hard to imagine that it is the least likely informed ones - the small investors - who are engaged in informed trading. One may also suspect that the higher volume in the smaller-investor category is actually due to sophisticated traders splitting their orders. While we cannot conclusively disprove this conjecture with the available data, we reject it on the intuitive level: This category consists of transactions that are less than 100 contracts in size and it is doubtful that the informed traders (who arguably have larger stakes) would go that far by submitting numerous odd-numbered orders. A stronger rejection of the order-splitting conjecture comes in the next section where we show that the option turnovers don't predict returns.

Though striking and substantial in magnitude, the variations in the abnormal proportions may not be statistically significant. To address this concern, we tabulate in Tables 6 and 7 the abnormal proportions and perform statistical tests. It is seen that most of the abnormal proportions are statistically different from zero. It is also evident that the magnitude of all abnormal proportions (other than those of the small investors) is generally very small, around 1% or lower. Specifically, the large investors and brokerage firms all trade less relative to the control period, leaving no indication whatsoever of informed trading. Finally, if small investors are heightening their trading activities while other investors are curtailing theirs, who act as the counterparty for small investors? Clearly the market makers must be on the other side of the trades.

Collectively, Figure 1 and Tables 6 and 7 show convincingly that option trading around earnings announcements is of speculative nature and mostly driven by small investors. More importantly, small investors are much more active than others. Therefore the answer to the question posed in the section title is a resounding "No". This in turn reinforces the conclusion obtained from the broader sample in Table 5 that option trading around earnings announcements is not driven by information; it is mostly driven by speculation or opinion dispersion.

3.3. Information trading versus speculation around earnings announcements - a refined test

So far, we have only examined the trading patterns around earnings announcements. We controlled for returns in Table 5 while examining trading patterns since price movements are the ultimate realizations of private information. In this section, we refine the study by statistically testing if turnovers can predict stock returns, or equivalently, if trading is due to information. If options are used by informed traders, then option turnovers should predict future stock returns. In particular, a higher call option turnover should predict higher future stock returns and a higher put option turnover should predict lower future stock returns. If, on the other hand, options are used to speculate on the temporary trend in stock prices, we should only see a strong contemporaneous correlation between option turnovers and returns; there should be no relation between current option turnovers and future stocks returns. The lack of predictability of future returns via option turnovers will also invalidate the conjecture of informed traders splitting their orders. We will employ sorting and regressions to carry out the investigation.

As before, we still define the control period as [-42, -23] and day 0 as the announcement date.

Unlike before, we now define the pre-announcement period as [-10,-3] and the post-announcement period as [+3, +10]. The definition of slightly longer pre- and post-announcement periods is for reliability when calculating average returns and turnover; the wider window of the announcement period [-2, +2] is to ensure that pre- and post-announcement periods do not include actual announcements due to recording errors. We first calculate the average daily turnover and return for each period, and then obtain the abnormal turnover and return for the pre- and post-announcement periods by subtracting the corresponding quantities of the control period. The abnormal returns are sorted into quintiles by either the pre- or the post-announcement period turnover. For each sorting exercise, we report the mean and its t-value of each quintile's abnormal return. We also report t-values for the pair-wise, equal-mean tests. Table 8 contains the results.

Panel A contains the sorting results for stocks. We see that the post-announcement abnormal returns increase monotonically with the pre-announcement turnovers. Except for the lowest-turnover quintile, all the quintile returns are statistically different from zero. Moreover, the difference in abnormal returns between the highest and lowest turnover quintiles is highly significant (t-$value = 7.516$). In contrast, we do not observe a monotonic association between pre-announcement turnovers and pre-announcement abnormal returns. Together, the results suggest that the apparent predictability of turnovers is unlikely due to investors betting on the momentum of stock price movements alone. There seems to be informed trading in stocks. In contrast, when sorting the post-announcement abnormal returns by the post-announcement turnover, we see a clear monotonic relation, indicating elements of speculation or momentum trading.

Similar speculative trading in the post-announcement period is also observed for calls (Panel B) and puts (Panel C). However, the sorting exercises using the pre-announcement option turnovers lead to results quite different from stocks'. To begin, for call options in Panel B, the post-announcement abnormal returns are by no means monotonic, although the return for the highest-turnover quintile is statistically higher than that of the lowest quintile (t-$value = 2.529$). More importantly, the pre-announcement abnormal returns increase monotonically with the turnover, suggesting that the apparent, weak predictability of pre-announcement turnovers may be due to momentum trading or speculation. For put options in Panel C, although the post-announcement returns are monotonic, the association between turnovers and returns in the pre-announcement period is also much stronger, again suggesting potential speculation instead of informed trading.

In summary, the sorting results in Table 8 can be interpreted in two ways. For one, they suggest that the pre-announcement turnovers of stocks, calls and puts can all predict post-announcement returns, confirming informed trading in both the stock market and the option market. For another, the results could suggest that there is informed trading in the stock market but not in the option market; the apparent predictive power of option turnovers might be a result of option traders riding on the existing trend of the stock price movements. Below, we use regression analyses to confirm the latter interpretation.

To this end, for each market (stocks, calls and puts), we run five regressions. The dependent variable for Regressions 1 to 3 is the post-announcement abnormal return. The independent variables are, respectively, the pre-announcement abnormal return (Regression 1), the pre-announcement abnormal turnover (Regression 2), and both in the regression (Regression 3). Regressions 4 and 5 are two-pass regressions. For Regression 4, we first remove the effect of pre-announcement abnormal return on the post-announcement abnormal return by regressing the latter on the former; we then regress the residuals on the pre-announcement turnovers. This is to see if the turnover still has predictive power once we purge the momentum in returns. Regression 5 is done in a similar fashion except that we first purge the effect of turnover and see if the return momentum continues. This regression is done for completeness. To enhance testing power, we aggregate the observations into 100 equal groups by first sorting the pre-announcement abnormal turnover (for either stocks, calls or puts) and then calculating the associated abnormal turnover and abnormal returns for each group. Regressions are performed on the 100 groups. Table 9 reports the results.[6]

The existence of informed trading in stocks is strongly confirmed. The pre-announcement abnormal turnover alone explains 40% of the variation in the post-announcement abnormal returns. The incremental explanatory power of the pre-announcement abnormal returns is minimal (the adjusted R^2 goes from 40.33% to 42.49%). More, after removing the return continuation effect,

[6]We also examined other grouping sizes (30, 50 and 200). The results remain the same qualitatively.

the pre-announcement abnormal turnover can still explain 34.79% of the variation in the post-announcement abnormal returns. Informed trading in stocks is confirmed consistently throughout the study.

The regression results for calls and puts are completely different from stocks'. For calls, the pre-announcement abnormal return has a much higher explanatory power than the abnormal turnover (R^2 of 11.39% versus 5.29%), and the incremental explanatory of the latter is almost zero (the adjusted R^2 goes up by only 0.16%). Once we remove the impact of pre-announcement returns, the pre-announcement abnormal turnover has zero explanatory power for the post-announcement returns ($R^2 = -0.71\%$). Similar and slightly stronger results hold true for put options (the adjusted R^2 actually goes down in Regression 3). It is clear that, the apparent predictive power of pre-announcement abnormal turnovers of options is purely spurious. We can also infer that the more active trading in the "small investor" category observed previously is not due to informed traders splitting their orders. All said, option trading around earnings announcements is mostly driven by speculation on the continuation of return momentums.

3.4. Reconciling with the existing literature

To this point, we have shown that, both in normal times and around earnings announcements, option trading is mostly driven by opinion dispersion while stock trading is driven by both information and opinion dispersion. To some extent, our findings on option trading are consistent with Stephan and Whaley (1990), Vijh (1990), Chan, Chung and Johnson (1993), and Chan, Chung and Fong (2002) in that these authors found that the option market either doesn't lead the stock market (Vijh, 1990; Chan, Chung and Johnson, 1993; and Chan, Chung and Fong, 2002) or is led by it (Stephan and Whaley, 1990). While all these studies focused on the information role of options on an intraday basis, we emphasize the role of opinion dispersion at a daily and weekly frequency. So our research compliments the above studies.

In contrast, our findings somewhat contradict the empirical evidence in Amin and Lee (1997), Easly, O'Hara and Srinivas (1998), Cao, Chen and Griffin (2005), and Pan and Poteshman (2006). Easly, O'Hara and Srinivas (1998) showed that the total option volumes do not predict stock prices whereas the option volumes associated with "positive news" (i.e., buying calls and writing puts) or "negative news" (i.e., writing calls and buying puts) do lead stock prices. They therefore concluded that "option markets are a venue for information-based trading". Their study is based on intraday data while ours on daily or weekly. Moreover, there are outstanding puzzles in their results (see pages 461-462 in their paper). In addition, Chan, Chung and Fong (2002) showed that after controlling for the stock returns, the predictive power of the signed option volume disappears.

Amin and Lee (1997) found that traders initiate a greater proportion of long positions in options before good earnings news, suggesting evidence of informational trading (long position means buying calls and writing puts while short position means the opposite). Certain aspects of their findings do not appear readily intuitive though. For instance, the proportions of long positions are actually higher before both good news and bad news (54.8% and 53.2%, respectively); by the same token, short positions are also higher before both types of news. They arrived at their conclusion by contrasting 54.8% and 53.2%, saying that the long positions increase more before good news than bad news. As a matter of fact, the higher proportions of both long and short positions before any type of news are consistent with trading based on differences of opinion or speculation.

By examining option trading prior to takeovers, Cao, Chen and Griffin (2005) found that the volume imbalance in calls can predict returns in the pre-announcement period but not other periods. Two points are worth noting. First, they found that the call option volume and put option volume both increase in the pre-announcement period. Moreover, the biggest increase in buyer-initiated volumes occurs in both out-of-the-money calls and out-of-the-money puts. This means that some people are betting positively and some are betting negatively, consistent with speculation. Second, they argued that if trading is simply driven by different opinions, then buyer- and seller-initiated volumes should increase by similar amount; the fact that there is more buyer-initiated trading means that people anticipate good news. This line of reasoning overlooks two important facts about takeovers: 1) price run-ups are prevalent prior to takeover announcements (Keown and Pinkerton, 1981; Jarrel and Poulsen, 1989; and Schwert, 1996), and 2) there are usually speculations in the media before the announcement (Schwert, 1996). In other words, the more buyer-initiated trading is also consistent with speculation in this context. In fact, their findings for the post-announcement period lend even stronger support for speculation: The trading volume of both calls and puts is much higher compared with the non-event period and it fails to predict the takeover outcomes.

Pan and Poteshman (2006) presented perhaps the most convincing evidence of informed trading in options. Using a proprietary dataset similar to our CBOE Open/Close data, they showed that the put-call ratio based on buy-to-open volumes ("open-buy" in short) can predict next day's or next week's stock returns. To reconcile our findings with theirs, it is useful to recognize the following: 1) our study and others (e.g., Stephan and Whaley, 1990; and Chan, Chung and Fong, 2002) find evidence of information trading in the stock market but not in the option market, and 2) any apparent, predictive power of option volumes may simply be a manifestation of the information revelation in the stock market. In a more general vein, it is quite likely that option traders simply take cues from the stock market and trade accordingly. We demonstrate supporting evidence below.

Using the CBOE's Open/Close data from January 1, 2006 to July 31, 2006, we first replicate the main results of Pan and Poteshman (2006, Table 4) and then show that once we control for the stock's order imbalance and other factors, the predictive power of the open-buy put-call ratio disappears. Following Pan and Poteshman (2006), we run predictive, cross-section regressions on a daily basis. The dependent variable is the residual from the four-factor model of market, size, value and momentum while the main regressor is the open-buy put-call ratio which is calculated as the put volume divided by the sum of put and call volumes, all originated as buy-to-open positions. The three control variables are the stock's turnover, the stock's bid-ask spread and the past five-day return.[7] Table 10 contains the results. Even though our sample is much shorter than the sample in Pan and Poteshman (2006), the coefficient for the put-call ratio in the first four OLS regressions is negative and highly significant, consistent with Pan and Poteshman (2006). Next, we add more control variables to the specification of Pan and Poteshman (2006) and show that the explanatory power of the put-call ratio disappears.

[7] Pan and Poteshman (2006) used the raw five-day returns whereas we use residual returns to be consistent with the simultaneous regressions we run later. The results using the raw five-day returns are almost identical as far as t-values are concerned.

To this end, we first consider the current and lagged residual returns of the stock to take care of the potential serial correlations. We then consider the impact of order imbalance ("OIMB" in short) on returns.[8] Based on the theoretical predictions on the price impact of order imbalances, Chordia and Subrahmanyam (2004) showed empirically that the next period's return is positively correlated with this period's OIMB (due to price pressure) and negatively correlated with previous periods' OIMB (due to reversals). They also found that the reversal effect is much stronger for large firms. Following Chordia and Subrahmanyam (2004), we consider four lags of OIMB. We also include the size and size-OIMB interaction terms in light of the aforementioned findings. We anticipate a negative sign for the size interaction with the current period's OIMB since the stronger reversal effect for large firms will counter the price pressure effect. Our key prediction though is with respect to the put-call ratio. We hypothesize that option traders take cues from OIMB before establishing option positions. If this is the case, the coefficient of the put-call ratio should be insignificant after we add the control variables involving order imbalances. The last four OLS regressions in Table 10 confirm our priors. The put-call ratio coefficient is insignificant and its sign varies depending on the specification.

In order to fully back up our claim that option traders take cues from the stock market instead of the other way around, we need to take care of the potential endogeneity of the three key variables: the residual return (R_t), the order imbalance ($OIMB_t$) and the put-call ratio (PC_Ratio_t). To this end, we run the following cross-section, simultaneous regressions daily via the three-stage least squares:

$$
\begin{aligned}
R_t &= (PC\_Ratio_t, OIMB_t, PC\_Ratio\_lags, R\_lags, OIMB\_lags), \\
PC\_Ratio_t &= (R_t, OIMB_t, PC\_ratio\_lags, R\_lags, OIMB\_lags, \\
&\qquad LnSize_t, OIMB_t * LnSize_t, OIMB\_lags * LnSize_t), \\
OIMB_t &= (R_t, PC\_Ratio_t, PC\_Ratio\_lags, R\_lags, OIMB\_lags),
\end{aligned}
\tag{3.5}
$$

where R_lags and PC_ratio_lags stand for the first two lags of the residual return and the put-call ratio respectively, $OIMB\_lags$ stands for the first four lags of order imbalance and $LnSize_t$ is the

[8] In this study, OIMB is defined as the difference between the numbers of buyer- and seller-initiated orders scaled by the total number of orders during the day. The classification of orders is done using the Lee-Ready algorithm (Lee and Ready, 1991).

logarithm of firm size for the current period. We add the interaction terms in the put-call ratio equation to capture the possibility that investors may use options to profit from the reversals. For instance, for a larger firm with a stronger reversal effect, a higher OIMB today together with a positive return (due to price pressure) would most likely mean a negative return tomorrow, which would lead to more buying of put options today. In other words, we anticipate a positive sign for the interaction term involving the first lag of OIMB. The last three columns of Table 10 confirm our priors. In contrast to the OLS regressions, the simultaneous equations provide much sharper results, especially for the impact of OIMB on returns. The most relevant are the strong predictive power of the contemporaneous and lagged terms of order imbalance and the absence of the predictive power of the first lag of the put-call ratio.

All told, we believe that the apparent predictive power of the put-call ratio is just a manifestation of option traders reacting to what has happened in the stock market, a behavior consistent with speculation.

4. Conclusion

This paper investigates the motive of option trading and shows that the main driving force of option volume is differences of opinion. Our findings are different from the current literature that attempts to link option trading to information (e.g., Amin and Lee, 1997; Easly, O'Hara and Srinivas, 1998; Cao, Chen and Griffin, 2005; and Pan and Poteshman, 2006). Our general conclusion is based on three empirical findings. First, for the sample period of January 1, 1996 to December 31, 2006, we show via both cross-section and time-series regressions that option trading is significantly explained by such proxies of opinion dispersion as the number of analysts, market sidedness, earnings forecast dispersion and stock return volatility. While informed trading is present in stocks as is speculative trading, informed trading is not detected in options.

Second, the trading patterns around earnings announcements confirm the broader evidence from the cross-section and time-series regression analyses. Option trading increases significantly around earnings announcements and the increase is attributed to smaller, retail investors engaging in speculative trades.

Third, the abnormal option turnovers and abnormal stock returns are significantly related (positively for calls and negatively for puts) in both the pre- and the post-announcement periods, and so are the pre-announcement abnormal turnovers and the post-announcement abnormal returns. However, once we control for the pre-announcement returns, the pre-announcement turnovers no longer predict the post-announcement returns. Hence, option trading doesn't appear to be driven by information around earnings announcements; instead, it is mostly driven by speculation.

As far as explaining the day-to-day option trading activities is concerned, be they in usual times or around earnings announcements, differences of opinion or speculation are by far the most important driving forces. Nonetheless, it would be premature to completely rule out informed trading in options. After all, there are prosecutions of persons engaged in insider-trading using options. Our study does imply though that information trading in options is far from being a routine affair as previous researchers have believed. Such trading is so rare that it is beyond the detection of the usual empirical apparatus.

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Table 1: Summary statistics

This table shows the summary statistics for the main variables used in the regression analysis. The sample period is from January 1, 1996 to December 31, 2006. Since the regressions are based on weekly data, we first aggregate daily observations into weekly by simple averaging. Correlations are calculated using weekly observations and are averaged across time. In each entry of the correlation matrix, the upper number is the average correlation and the lower number the *t*-value. All *t*-values are significant at the 1% level. The panel at the bottom of the table presents the mean, median, standard deviation, minimum and maximum of each variable prior to detrending. Volatility (Avolatility) is the weekly average of daily return squared. See the appendix for other variable definitions.

	Alog_price	Alog_size	APIN	Astock_pba	Aoption_pba	Alog_num_analyst	Asidedness	ADISP	Ascaled_disp	Avolatility
Alog_price	1.00									
Alog_size	0.61	1.00								
	130.97									
APIN	-0.23	-0.47	1.00							
	-49.24	-144.08								
Astock_pba	-0.38	-0.33	0.14	1.00						
	-65.66	-52.96	26.47							
Aoption_pba	-0.42	-0.43	0.27	0.29	1.00					
	-108.34	-212.41	111.36	66.97						
Alog_num_analyst	0.19	0.41	-0.29	-0.18	-0.26	1.00				
	35.64	178.45	-122.47	-53.15	-140.48					
Asidedness	0.23	0.38	-0.34	-0.16	-0.22	0.27	1.00			
	36.41	57.66	-85.75	-27.98	-41.89	60.33				
ADISP	0.07	0.04	-0.04	0.01	-0.04	0.04	0.05	1.00		
	29.44	25.62	-25.28	3.62	-26.16	22.69	26.06			
Ascaled_DISP	-0.18	-0.15	0.05	0.12	0.09	-0.05	-0.02	0.66	1.00	
	-86.95	-92.34	33.36	42.50	49.76	-36.30	-6.77	166.33		
Avolatility	-0.11	-0.10	0.02	0.05	-0.01	-0.02	0.05	-0.01	0.04	1.00
	-37.23	-43.66	15.15	21.31	-7.08	-15.70	25.15	-4.63	16.90	
Mean	3.2339	21.1960	0.1431	0.0096	0.2239	1.3734	-0.0715	0.0325	0.0013	0.0011
Median	3.2819	21.0788	0.1334	0.0069	0.1989	1.4674	-0.0330	0.0153	0.0006	0.0004
STD	0.7039	1.5420	0.0731	0.0098	0.1324	0.9012	0.2875	0.0649	0.0031	0.0052
Min	0.6574	14.8726	0.0000	0.0001	0.0118	0.0000	-1.0000	0.0000	0.0000	0.0000
Max	6.3102	27.1331	1.0000	0.4831	1.9273	3.7377	1.0000	6.1568	0.3007	2.7228

Table 2: Cross-section regressions of turnover on proxies of information asymmetry and differences of opinion

This table presents results from Fama-MacBeth regressions. The stock turnover (Alog_stock_turnover) or the option turnover (Alog_option_turnover) of the current period is regressed on the previous period's proxies of information asymmetry (Alog_size, APIN, Astock_pba and Aoption_pba) and differences of opinion (Asidedness, ADISP and Avolatility) together with control variables. The predictive cross-section regression is run each week and the regression coefficients are averaged across time. We first run a univariate regression for each independent variable and then run five versions of multivariate regressions. In each entry, the upper number is the coefficient average and the lower number the *t*-value which is based on Newey-West adjustment. The adjusted R^2 is averaged across the weekly regressions. Significance levels of 10%, 5% and 1% are indicated by *, **, and *** respectively. Intercepts and associated *t*-values are omitted for brevity. See the appendix for variable definitions.

	Univariate regressions		Multivariate regressions					
Explanatory variables	coeff & t-value	Adj R^2 (%)	1	2	3	4	5	6
Panel A. Dependent variable: Alog_stock_turnover								
Alog_size	-0.13							-0.10
	-28.93 ***	5.51						-23.48 ***
APIN	0.36					0.27	0.20	
	3.81 ***	0.61				3.21 ***	2.59 ***	
Astock_pba	-15.46				0.87			
	-17.32 ***	2.43			1.74 *			
Alog_num_analyst	0.14		0.16	0.13	0.13	0.14	0.14	
	27.60 ***	1.15	34.07 ***	16.29 ***	18.44 ***	22.67 ***	25.48 ***	
Asidedness	0.50			0.39	0.41	0.41	0.43	
	10.78 ***	4.76		9.64 ***	10.05 ***	9.60 ***	9.79 ***	
ADISP	0.22			0.92	0.95	0.99	1.02	0.41
	6.71 ***	0.03		13.69 ***	20.26 ***	21.30 ***	23.02 ***	13.85 ***
Avolatility	56.62			47.81	44.86	35.23	33.72	19.75
	31.07 ***	3.62		3.96 ***	4.57 ***	12.99 ***	12.47 ***	12.24 ***
Alog_price	-0.07						-0.05	
	-6.81 ***	1.13					-2.34 **	
Return_positive	3.64		5.92	3.81	3.93	4.24	4.20	4.54
	27.12 ***	3.23	42.00 ***	7.02 ***	9.46 ***	23.56 ***	23.30 ***	37.33 ***
Return_negative	-4.93		-7.31	-5.81	-5.99	-5.94	-5.80	-5.72
	-32.14 ***	3.94	-39.31 ***	-19.19 ***	-29.18 ***	-28.68 ***	-28.44 ***	-39.32 ***
Adjusted R^2 (%)			10.52	12.85	13.10	13.07	13.64	13.37
Panel B. Dependent variable: Alog_option_turnover (call and put options combined)								
Alog_size	0.84							0.87
	97.02 ***	15.10						96.15 ***
APIN	-12.17					-12.31	-10.44	
	-37.57 ***	6.05				-41.87 ***	-35.34 ***	
Astock_pba	-96.87			-67.52	-28.62			
	-29.07 ***	5.50		-32.49 ***	-14.93 ***			
Aoption_pba	-14.36				-12.09			
	-76.09 ***	23.00			-62.77 ***			
Alog_num_analyst	1.40		1.28	1.16	0.78	1.07	1.00	
	42.32 ***	7.50	47.54 ***	45.44 ***	38.81 ***	43.95 ***	39.57 ***	
Asidedness	2.96		2.43	2.19	1.68	2.00	1.60	
	13.20 ***	8.11	13.24 ***	13.35 ***	12.42 ***	11.72 ***	10.25 ***	
ADISP	2.67		2.34	2.18	1.30	2.59	2.11	1.96
	19.79 ***	0.25	15.00 ***	14.83 ***	7.24 ***	17.65 ***	15.46 ***	17.08 ***
Avolatility	68.68		110.27	163.96	103.17	125.09	165.73	130.03
	18.13 ***	0.51	12.83 ***	18.98 ***	5.16 ***	15.10 ***	20.02 ***	28.68 ***
Alog_price	1.09						0.73	
	32.78 ***	6.63					13.35 ***	
Adjusted R^2 (%)			14.49	17.14	30.05	18.07	20.42	16.71

Table 3: Time-series regressions of turnover on proxies of information asymmetry and differences of opinion

This table presents results from time-series regressions. The stock turnover (Alog_stock_turnover) or the option turnover (Alog_option_turnover) is regressed on the lagged proxies of information asymmetry (APIN, Astock_pba and Aoption_pba) and differences of opinion (Asidedness, Ascaled_DISP, |Ascaled_change_DISP| and Avolatility) together with lagged control variables. The predictive time-series regression is run for reach stock using weekly observations and the regression coefficients are averaged across stocks. To avoid unreliable estimates from regressions with too few observations, we require that each stock must have data for more than one year. To further minimize the undue impact of potential outlier estimates, the coefficients are averaged using the inverse of the standard error as weight. We first run a univariate regression for each independent variable (Regressions 1 through 9 for stocks and 1 through 8 for options) and then run one multivariate regression (Regression 10 for stocks and Regression 9 for options). In each entry, the upper number is the coefficient average and the lower number the *t*-value. The adjusted R^2 is averaged across the time-series regressions. Significance levels of 10%, 5% and 1% are indicated by *, **, and *** respectively. Intercepts and associated *t*-values are omitted for brevity. See the appendix for variable definitions.

Panel A. Dependent variable: Alog_stock_turnover

Explanatory variables	1	2	3	4	5	6	7	8	9	10
APIN	-0.05									0.02
	-1.24									0.46
Astock_pba		0.61								0.56
		2.66 ***								2.06 **
Alog_num_analyst			0.00							0.01
			1.36							3.40 ***
Asidedness				0.16						0.09
				18.73 ***						11.18 ***
Ascaled_DISP					7.30					0.01
					4.21 ***					0.26
|Ascaled change_DISP|						62.50				0.59
						24.00 ***				16.06 ***
Avolatility							37.83			31.45
							32.93 ***			17.38 ***
Return_positive								0.55		0.97
								22.13 ***		22.44 ***
Return_negative									-1.89	-2.40
									-57.77 ***	-46.51 ***
Adjusted R^2 (%)	11.18	16.57	10.54	10.65	11.12	10.75	10.75	11.54	10.20	11.40

Panel B. Dependent variable: Alog_option_turnover (call and put options combined)

Explanatory variables	1	2	3	4	5	6	7	8	9
APIN	-0.11								-0.12
	-0.78								-0.60
Astock_pba		-9.65							-8.11
		-11.73 ***							-7.83 ***
Aoption_pba			-3.32						-2.63
			-40.75 ***						-25.21 ***
Alog_num_analyst				0.09					0.08
				8.86 ***					6.36 ***
Asidedness					0.27				0.14
					9.39 ***				5.02 ***
Ascaled_DISP						8.41			0.02
						1.44			0.28
|Ascaled change_DISP|							34.48		0.32
							4.55 ***		2.89 ***
Avolatility								49.81	77.34
								14.40 ***	12.64 ***
Adjusted R^2 (%)	7.01	6.63	6.62	6.92	6.67	6.34	6.53	7.83	9.34

Table 4: Time-series regressions of options' relative trading volume on proxies of information asymmetry and differences of opinion

This table presents results from time-series regressions. The variable Alog_scaled_ratio (which is the option volume divided by the sum of the option volume and stock volume upon scale adjustment as described in the appendix) is regressed on the lagged proxies of information asymmetry (APIN, Astock_pba and Aoption_pba) and differences of opinion (Asidedness, Ascaled_DISP, |Ascaled_change_DISP| and Avolatility) together with the lagged number of analysts (Alog_num_analyst). The predictive time-series regression is run for reach stock using weekly observations and the regression coefficients are averaged across stocks. To avoid unreliable estimates from regressions with too few observations, we require that each stock must have data for more than one year. To further minimize the undue impact of potential outlier estimates, the coefficients are averaged using the inverse of the standard error as weight. We first run a univariate regression for each independent variable (Regressions 1 through 8) and then run one multivariate regression (Regression 9). In each entry, the upper number is the coefficient average and the lower number the *t*-value. The adjusted R^2 is averaged across the time-series regressions. Significance levels of 10%, 5% and 1% are indicated by *, **, and *** respectively. Intercepts and associated *t*-values are omitted for brevity. See the appendix for variable definitions.

Explanatory variables	1	2	3	4	5	6	7	8	9
APIN	0.04								0.03
	0.47								0.26
Astock_pba		-3.99							-0.30
		-7.14 ***							-0.44
Aoption_pba			-3.19						-2.82
			-50.24 ***						-35.05 ***
Alog_num_analyst				0.08					0.07
				12.13 ***					8.36 ***
Asidedness					0.20				0.13
					10.80 ***				6.84 ***
Ascaled_DISP						3.62			0.01
						0.78			0.19
|Ascaled change_DISP|							26.57		0.31
							0.00		4.12 ***
Avolatility								9.78	14.18
								4.64 ***	3.83 ***
Adjusted R^2 (%)	9.90	9.25	11.83	9.33	10.33	9.33	8.91	9.00	14.48

Table 5: Comparing turnovers around earnings announcements while controlling for the level of stock returns

This table is in the same spirit as Table 2 in Kandel and Pearson (1995). Quarterly earnings announcements for the period of January 1, 1996 to December 31, 2006 are used. We first define the control, non-event, pre-announcement, at-announcement, and post-announcement periods as [-42, -23], [-22, -5], [-4, -2], [-1, +1] and [+2, +10], respectively with day 0 being the announcement day. Each period is then divided into 3-day segments and the total stock return and average turnover (in logarithm) are calculated for each segment. We subtract the control period's average turnover from those of other periods and call the resulting differences abnormal turnovers. The raw-return domain is divided into 22 mutually exclusive ranges (as indicated in the first column) and the corresponding abnormal turnovers are tabulated. For brevity, we only report the non-event period abnormal turnover (Non-event) and the three pair-wise differences in abnormal turnovers: (Pre – Non), (At – Non), and (Post – Non). (Kandel and Pearson (1995) normalize the event-period volumes as ratios relative to the non-event period volumes. We instead use differences to facilitate testing and to avoid large ratios due to small dividers.) The asterisks next to each column indicate the significance of *t*-values for the test that the turnover difference is equal to zero (*, **, and *** correspond to 10%, 5% and 1% significance levels respectively).

	Stocks				Calls				Puts			
Return range	Non-event	Pre- Non	At - Non	Post - Non	Non-event	Pre- Non	At - Non	Post - Non	Non-event	Pre- Non	At - Non	Post - Non
[-5.0% < R]	0.260	-0.028 **	0.374 ***	0.037 ***	0.628	0.231 ***	1.477 ***	0.031	1.133	0.381 ***	1.665 ***	0.044
[-0.5% ≤ R < -4.5%]	0.124	-0.022	0.338 ***	0.039 **	0.342	0.310 **	1.442 **	0.036	0.825	0.301 **	1.254 ***	0.003
[-4.5% ≤ R < -4.0%]	0.086	-0.045 **	0.291 ***	0.069 ***	0.231	0.174	1.398 ***	0.254 **	0.614	0.243 *	1.564 ***	0.206 **
[-4.0% ≤ R < -3.5%]	0.056	-0.020	0.297 ***	0.090 ***	0.163	0.371 ***	1.407 ***	0.171 **	0.493	0.279 **	1.505 ***	0.303 ***
[-3.5% ≤ R < -3.0%]	0.037	-0.001	0.305 ***	0.097 ***	0.109	0.604 ***	1.443 ***	0.189 **	0.489	0.316 ***	1.411 ***	0.187 **
[-3.0% ≤ R < -2.5%]	0.018	-0.014	0.299 ***	0.082 ***	0.082	0.230 **	1.202 ***	0.167 **	0.381	0.205 **	1.350 ***	0.131 **
[-2.5% ≤ R < -2.0%]	0.001	0.009	0.275 ***	0.095 ***	-0.019	0.386 ***	1.230 ***	0.207 ***	0.256	0.415 ***	1.336 ***	0.215 ***
[-2.0% ≤ R < -1.5%]	-0.030	-0.021	0.294 ***	0.117 ***	-0.074	0.263 ***	1.298 ***	0.260 ***	0.198	0.409 ***	1.326 ***	0.196 ***
[-1.5% ≤ R < -1.0%]	-0.044	-0.021 *	0.302 ***	0.088 ***	-0.106	0.277 ***	1.300 ***	0.181 ***	0.079	0.243 ***	1.390 ***	0.152 ***
[-1.0% ≤ R < -0.5%]	-0.062	0.012	0.274 ***	0.107 ***	-0.132	0.394 ***	1.191 ***	0.094 **	-0.014	0.277 ***	1.331 ***	0.168 ***
[-0.5% ≤ R < 0.0%]	-0.070	0.024 **	0.296 ***	0.130 ***	-0.144	0.439 ***	1.327 ***	0.143 ***	-0.083	0.345 ***	1.364 ***	0.210 ***
[0.0% ≤ R < 0.5%]	-0.067	0.015	0.285 ***	0.108 ***	-0.115	0.251 ***	1.110 ***	0.182 ***	-0.120	0.355 ***	1.341 ***	0.141 ***
[0.5% ≤ R < 1.0%]	-0.048	-0.014	0.283 ***	0.103 ***	-0.030	0.287 ***	1.204 ***	0.139 ***	-0.077	0.398 ***	1.256 ***	0.113 **
[1.0% ≤ R < 1.5%]	-0.044	-0.004	0.300 ***	0.123 ***	-0.002	0.338 ***	1.130 ***	0.209 ***	-0.137	0.312 ***	1.331 ***	0.242 ***
[1.5% ≤ R < 2.0%]	-0.018	0.011	0.282 ***	0.113 ***	0.086	0.347 ***	1.379 ***	0.257 ***	-0.094	0.405 ***	1.278 ***	0.194 ***
[2.0% ≤ R < 2.5%]	0.010	0.005	0.271 ***	0.116 ***	0.255	0.365 ***	1.224 ***	0.224 ***	0.008	0.435 ***	1.388 ***	0.161 ***
[2.5% ≤ R < 3.0%]	0.031	-0.026	0.288 ***	0.118 ***	0.215	0.314 ***	1.366 ***	0.386 ***	-0.046	0.332 ***	1.484 ***	0.244 ***
[3.0% ≤ R < 3.5%]	0.051	-0.019	0.286 ***	0.130 ***	0.364	0.267 **	1.284 ***	0.383 ***	0.074	0.260 **	1.445 ***	0.209 ***
[3.5% ≤ R < 4.0%]	0.077	-0.010	0.262 ***	0.117 ***	0.473	0.145	1.177 ***	0.244 ***	0.063	0.344 ***	1.432 ***	0.184 **
[4.0% ≤ R < 4.5%]	0.098	0.003	0.312 ***	0.144 ***	0.474	0.312 **	1.416 ***	0.358 ***	0.128	0.156	1.280 ***	0.251 ***
[4.5% ≤ R < 5.0%]	0.113	-0.040	0.249 ***	0.119 ***	0.605	0.253 *	1.025 ***	0.311 ***	0.109	0.304 **	1.136 ***	0.187 **
[5.0% ≤ R]	0.248	0.005	0.303 ***	0.103 ***	0.973	0.227 ***	1.268 ***	0.379 ***	0.407	0.313 ***	1.563 ***	0.143 ***

Table 6: Trading activities of call options around earnings announcements

This table reports the trading activities of call options around earnings announcements broken down by trade type, size and type of trade initiator. The CBOE's Open/Close data for the period of January 1, 2006 to July 31, 2006 are used. The dataset reports, on a daily frequency, the breakdown of trading volumes for each option by trade type (buy/sell/open/close), trade size (small/medium/large) and initiator (firm/customers). "Firm" stands for proprietary trading by brokerage firms on their own accounts while "customers" stands for all other trading except for market makers (a "customer" can be a retail investor or an institutional investor who uses the service of a brokerage firm). The size of trade (in the number of contracts) is defined as small < 100, 100 ≤ medium ≤ 199 and large ≥ 200. The size classification is not available for firms. For our analysis, we first calculate the average proportion of each type/size/initiator combination relative to the total volume in the control period which is [-42, -23]. We then calculate the abnormal proportions for each day around the earnings announcement by subtracting the corresponding proportion in the control period. Day 0 corresponds to the announcement day. The table reports the abnormal proportions in percentage form. The asterisks next to each column indicate the significance of *t*-values for the test that the abnormal proportion is equal to zero (*, **, and *** correspond to 10%, 5% and 1% significance levels respectively). The column headings signify the 16 combinations of trade type, size and initiator. The first letter signifies either customers (C) or firms (F); the second letter indicates open (O) or close (C); the third letter indicates buy (B) or sell (S); and the subscript indicates the size (SM: small, MD: medium, or LG: large).

	Panel A. Transactions to open positions								Panel B. Transactions to close positions							
Event_day	COB_SM	COB_MD	COB_LG	FOB	COS_SM	COS_MD	COS_LG	FOS	CCB_SM	CCB_MD	CCB_LG	FCB	CCS_SM	CCS_MD	CCS_LG	FCS
-10	6.54 ***	-0.87 *	-2.06 ***	-1.42 **	1.40	-1.35 ***	-3.73 ***	-1.70 ***	4.07 ***	-0.52 **	-0.80 **	-0.60 **	3.91 ***	-0.69 *	-1.62 ***	-0.55 **
-9	5.56 ***	-1.01 **	-1.44 ***	-0.57	2.52 *	-2.29 ***	-3.34 ***	-1.30 ***	1.52 **	-0.17	-0.85 ***	-0.71 ***	5.49 ***	-1.21 ***	-1.86 ***	-0.33
-8	7.21 ***	-0.94 **	-1.88 ***	-1.22 **	1.90	-2.27 ***	-3.36 ***	-1.10 **	1.86 **	-0.35	-1.13 ***	-0.65 **	5.29 ***	-1.10 ***	-1.73 ***	-0.52 *
-7	5.33 ***	-1.33 ***	-1.64 ***	-0.91	6.88 ***	-2.07 ***	-4.11 ***	-1.24 ***	2.35 ***	-0.29	-1.42 ***	-1.02 ***	2.94 ***	-0.86 ***	-1.98 ***	-0.64 ***
-6	4.12 ***	-0.25	-1.53 ***	-0.46	5.21 ***	-1.53 ***	-3.18 ***	-1.58 ***	1.42 **	-0.37	-0.91 ***	-0.84 ***	3.11 ***	-1.17 ***	-1.65 ***	-0.38
-5	8.55 ***	-0.75 *	-0.74	-0.64	2.29 *	-2.36 ***	-3.56 ***	-1.18 ***	-0.49	-0.48 *	-0.83 ***	-0.87 ***	3.21 ***	-0.17	-1.82 ***	-0.18
-4	7.57 ***	0.01	-1.41 ***	-1.54 **	2.36 *	-2.15 ***	-4.00 ***	-0.61	1.28	-0.49 **	-1.29 ***	-0.75 ***	3.27 ***	-0.70 *	-1.26 ***	-0.29
-3	12.91 ***	-0.86 **	-1.81 ***	-1.79 ***	1.93	-1.93 ***	-3.72 ***	-0.89 **	0.24	-0.70 ***	-1.02 ***	-0.69 ***	1.29	-0.70 **	-1.85 ***	-0.43 *
-2	15.04 ***	-0.66	-1.98 ***	-0.54	-1.58	-2.52 ***	-2.84 ***	-1.22 ***	-0.68	-0.30	-1.20 ***	-0.50 *	1.48 *	-0.57 *	-1.72 ***	-0.21
-1	20.22 ***	0.18	-1.01 **	0.04	-6.57 ***	-2.04 ***	-3.18 ***	-0.73 *	-2.26 ***	-0.51 **	-1.10 ***	-0.63 ***	-0.28	-0.79 ***	-1.49 ***	0.16
0	13.88 ***	-0.33	-1.29 ***	-1.43 **	-9.51 ***	-1.92 ***	-3.02 ***	0.99 *	-1.57 ***	-0.69 ***	-0.67 **	-0.37	5.91 ***	-0.11	-1.04 ***	1.15 ***
1	3.33 ***	-0.94 **	-2.41 ***	-3.30 ***	-5.49 ***	-1.69 ***	-2.60 ***	0.28	0.83	-0.45 **	-1.03 ***	-0.27	13.18 ***	0.49	-0.46	0.53
2	4.14 ***	-0.81 **	-2.42 ***	-3.76 ***	0.36	-2.20 ***	-2.87 ***	-1.01 **	2.26 ***	-0.46 **	-1.14 ***	0.01	8.95 ***	0.30	-1.44 ***	0.11
3	4.30 ***	-1.47 ***	-1.95 ***	-3.32 ***	0.81	-2.00 ***	-2.83 ***	-0.91 *	3.14 ***	-0.56 **	-1.37 ***	-0.56 **	8.82 ***	-0.41	-1.42 ***	-0.27
4	3.79 ***	-1.31 ***	-2.96 ***	-2.04 ***	2.98 **	-2.60 ***	-3.29 ***	-0.48	2.41 ***	-0.41	-0.83 **	-0.46 *	8.18 ***	-0.72 **	-1.98 ***	-0.28
5	3.86 ***	-1.78 ***	-2.43 ***	-3.61 ***	1.31	-1.72 ***	-3.52 ***	-0.77	4.21 ***	-0.51 *	-1.11 ***	-0.11	9.26 ***	-0.83 **	-1.98 ***	-0.27
6	4.23 ***	-1.61 ***	-1.91 ***	-2.58 ***	2.90 **	-2.20 ***	-3.67 ***	-2.04 ***	3.54 ***	-0.33	-1.29 ***	-0.81 ***	8.64 ***	-0.83 ***	-2.19 ***	0.16
7	4.14 ***	-1.14 ***	-1.53 ***	-2.14 ***	1.54	-2.10 ***	-3.84 ***	-0.94 *	3.34 ***	-0.93 ***	-1.15 ***	-0.70 ***	8.29 ***	-0.60	-2.00 ***	-0.25
8	4.43 ***	-1.34 ***	-2.39 ***	-3.37 ***	1.36	-2.10 ***	-3.12 ***	-0.93 *	3.34 ***	-0.22	-1.17 ***	-0.24	8.87 ***	-0.96 ***	-1.62 ***	-0.55 **
9	4.26 ***	-0.74	-2.50 ***	-3.00 ***	1.53	-2.60 ***	-3.28 ***	-1.15 **	4.55 ***	-0.45 **	-1.50 ***	-0.44 *	8.63 ***	-1.09 ***	-1.86 ***	-0.36
10	4.85 ***	-0.98 **	-2.95 ***	-3.25 ***	1.61	-1.66 ***	-3.26 ***	-1.62 ***	4.66 ***	-0.51 **	-1.20 ***	-0.55 *	7.16 ***	-1.00 ***	-0.99 **	-0.31

Table 7: Trading activities of put options around earnings announcements

This table is the counterpart of Table 6. It reports the abnormal proportions of put options around earnings announcements broken down by trade type, size and type of trade initiator. Please refer to Table 6 for detailed notes.

	Panel A. Transactions to open positions								Panel B. Transactions to close positions							
Event_day	COB_SM	COB_MD	COB_LG	FOB	COS_SM	COS_MD	COS_LG	FOS	CCB_SM	CCB_MD	CCB_LG	FCB	CCS_SM	CCS_MD	CCS_LG	FCS
-10	3.92 ***	-1.27 ***	-3.88 ***	0.01	4.91 ***	-2.17 ***	-2.46 ***	-2.88 ***	2.67 ***	-0.33	-1.23 ***	-0.73 **	5.73 ***	-0.57	-1.38 ***	-0.34
-9	5.20 ***	-1.35 ***	-3.73 ***	-1.16	5.89 ***	-2.36 ***	-2.95 ***	-2.65 ***	3.23 ***	-0.74 ***	-1.82 ***	-0.12	5.11 ***	-0.99 ***	-1.11 **	-0.45
-8	4.10 ***	-1.00 **	-3.04 ***	-1.27	4.48 ***	-1.83 ***	-2.86 ***	-1.86 ***	3.65 ***	-0.42	-1.41 ***	-0.60 *	4.45 ***	-0.50	-1.48 ***	-0.41
-7	7.92 ***	-0.76	-3.88 ***	-1.08	6.01 ***	-2.23 ***	-2.31 ***	-3.03 ***	2.88 ***	-0.49	-1.89 ***	-0.75 ***	3.33 ***	-1.29 ***	-1.64 ***	-0.78 **
-6	6.35 ***	-0.54	-3.35 ***	1.57	3.94 ***	-1.97 ***	-2.68 ***	-2.77 ***	0.38	-0.87 ***	-1.66 ***	-0.75 **	4.92 ***	-0.75 *	-1.72 ***	-0.11
-5	8.92 ***	-0.75 *	-2.76 ***	-0.47	1.85	-0.97 *	-2.25 ***	-2.20 ***	1.50 *	-0.41	-1.67 ***	0.01	2.14 **	-0.88 ***	-1.20 ***	-0.86 ***
-4	6.87 ***	-0.81 **	-3.03 ***	0.13	1.99	-1.45 ***	-2.50 ***	-1.29 *	2.48 ***	-0.52 *	-1.37 ***	-0.60 *	3.06 ***	-0.90 **	-1.35 ***	-0.73 **
-3	12.20 ***	-0.59	-2.84 ***	-1.83 **	2.72 *	-2.28 ***	-2.42 ***	-1.81 ***	0.98	-0.85 ***	-1.41 ***	-0.49	2.34 **	-0.90 ***	-1.65 ***	-1.17 ***
-2	14.17 ***	-0.44	-3.28 ***	1.02	-1.27	-1.90 ***	-1.85 ***	-1.45 **	-0.70	-0.26	-1.40 ***	-0.85 ***	1.50	-1.09 ***	-1.66 ***	-0.55
-1	18.31 ***	0.33	-2.66 ***	1.99 **	-6.85 ***	-2.00 ***	-1.61 ***	-1.00	-0.96	-0.04	-1.12 ***	-0.01	-1.71 **	-1.21 ***	-1.23 ***	-0.23
0	14.56 ***	0.64	-2.70 ***	-0.81	-7.52 ***	-1.91 ***	-1.67 ***	0.24	-1.07	-0.10	-1.39 ***	-0.59 *	2.92 ***	-0.28	-0.78 **	0.45
1	3.78 ***	-0.08	-3.63 ***	-3.16 ***	-2.90 **	-1.53 ***	-1.65 ***	-0.49	0.87	-0.83 ***	-1.06 ***	-0.82 ***	10.96 ***	0.42	-0.41	0.53
2	5.30 ***	-0.46	-3.35 ***	-3.53 ***	-3.24 **	-1.29 ***	-2.73 ***	-0.49	1.68 **	-0.44	-1.35 ***	-0.77 **	11.34 ***	-0.11	-0.99 **	0.42
3	2.97 **	-1.26 ***	-2.06 ***	-2.41 ***	0.95	-1.82 ***	-2.31 ***	-1.70 ***	1.76 *	-0.76 ***	-1.15 ***	-0.15	9.24 ***	0.19	-1.13 ***	-0.38
4	4.71 ***	-1.26 ***	-4.03 ***	-2.64 ***	-0.27	-2.49 ***	-2.07 ***	-1.46 **	1.90 **	-0.62 **	-1.34 ***	-0.26	10.68 ***	-0.14	-0.77	0.04
5	4.56 ***	-0.90 **	-3.03 ***	-4.12 ***	0.52	-1.73 ***	-3.05 ***	-1.75 ***	2.76 ***	-0.84 ***	-1.12 ***	0.21	10.08 ***	-0.89 **	-1.25 ***	0.55
6	5.45 ***	-0.70	-3.11 ***	-3.45 ***	0.18	-1.83 ***	-2.91 ***	-0.45	2.35 **	-1.11 ***	-1.54 ***	-0.80 **	10.50 ***	-0.72 *	-1.33 ***	-0.54
7	6.57 ***	-1.15 **	-3.82 ***	-2.18 ***	0.22	-2.82 ***	-2.72 ***	-1.14 *	3.91 ***	-0.96 ***	-1.30 ***	-0.95 ***	9.41 ***	-0.90 **	-1.40 ***	-0.78 **
8	6.20 ***	-0.93 *	-4.23 ***	-1.21	-0.58	-1.94 ***	-2.21 ***	-1.44 **	2.38 **	-0.72 **	-1.46 ***	-1.28 ***	9.71 ***	-0.09	-1.58 ***	-0.62
9	6.39 ***	-0.62	-3.70 ***	-2.33 ***	1.71	-2.52 ***	-2.96 ***	-1.64 ***	3.23 ***	-1.04 ***	-1.63 ***	-0.68 *	9.66 ***	-1.19 ***	-1.92 ***	-0.77 **
10	6.10 ***	-1.10 **	-2.65 ***	-0.91	0.08	-2.33 ***	-2.63 ***	-1.30 *	3.27 ***	-1.16 ***	-1.35 ***	-0.94 ***	7.30 ***	-0.61	-1.04 **	-0.73 **

Table 8: Association between abnormal turnover and abnormal stock returns around earnings announcements – evidence from sorting

This table presents abnormal stock returns before and after quarterly earnings announcements sorted by the abnormal turnover of stocks (Panel A), call options (Panel B) and put options (Panel C). The sample period is the same as in Table 5. Following Chae (2005), we define the pre-announcement period as [-10, -3] and the post-announcement period as [+3, +10] relative to the announcement day, 0. The control period of [-42, -23] is the same as in Table 5. Within each period, we calculate the average daily turnover and return, and obtain the abnormal turnover and return for the pre- or post-announcement period by subtracting the corresponding quantities of the control period. In all cases, we sort by the abnormal turnover and report the associated abnormal returns. The *t*-value is for the test that the mean abnormal return is equal to zero; the column with the heading "t-diff" contains *t*-values for the pair-wise mean-difference test. The first *t*-value is for the difference in returns between Quintile 2 and the smallest quintile; the second *t*-value is for the difference in returns between Quintiles 3 and 2, and so on; the last *t*-value is for the difference in returns between the largest and the smallest quintiles. Significance levels of 10%, 5% and 1% are indicated by *, **, and *** respectively.

	Sorting by pre-announcement turnover						Sorting by post-announcement turnover		
Abnormal	Post-annoucement abnormal return (%)			Pre-annoucement abnormal return (%)			Post-annoucement abnormal return (%)		
Turnover	Mean	t-value	t-diff	Mean	t-value	t-diff	Mean	t-value	t-diff
				Panel A: using stock abnormal turnover					
lowest	-0.008	-0.561	2.316 **	-0.058	-4.469 ***	2.436 **	0.019	1.398	0.609
2	0.037	2.836 ***	1.414	-0.014	-1.088	1.769 *	0.030	2.467 **	1.893 **
3	0.063	4.794 ***	0.144	0.019	1.408	0.677	0.064	5.112 ***	0.096
4	0.065	4.857 ***	3.970 ***	0.005	0.356	0.921	0.065	4.890 ***	2.643 **
highest	0.142	10.190 ***	7.516 ***	-0.016	-0.897	1.868 *	0.120	7.695 ***	4.840 ***
				Panel B: using call option abnormal turnover					
lowest	0.037	2.753 ***	1.714 *	-0.157	-11.918 ***	5.658 ***	-0.132	-10.556 ***	7.578 ***
2	0.070	5.109 ***	0.767	-0.050	-3.698 ***	1.200	0.002	0.132	3.369 ***
3	0.055	3.910 ***	0.097	-0.026	-1.806 *	1.529	0.064	4.693 ***	1.356
4	0.053	3.868 ***	1.663 *	0.005	0.354	7.325	0.090	6.621 ***	9.288 ***
highest	0.084	6.463 ***	2.529 **	0.164	10.171 ***	15.417 ***	0.276	18.768 ***	21.126 ***
				Panel C: using put option abnormal turnover					
lowest	0.125	8.676 ***	3.044 ***	0.099	6.934 ***	4.346 ***	0.166	12.090 ***	5.658 ***
2	0.065	4.729 ***	0.909	0.013	0.898	2.756 ***	0.060	4.601 ***	0.320
3	0.048	3.704 ***	0.700	-0.041	-3.039 ***	0.565 ***	0.054	4.131 ***	0.047
4	0.035	2.651 ***	0.487	-0.030	-2.024 **	3.538 ***	0.053	3.839 ***	4.409 ***
highest	0.026	1.902 *	5.045 ***	-0.106	-6.720 ***	9.637 ***	-0.034	-2.415 **	10.174 ***

Table 9: Association between abnormal turnover and abnormal stock returns around earnings announcements – evidence from regression analysis

This table presents regression results aimed at determining whether the pre-announcement abnormal turnovers contain information about future returns. For each category of trading (stocks, call options and put options), we run five regressions. The dependent variable for the first three regressions is the post-announcement abnormal return of the stock and the independent variables are the pre-announcement abnormal stock return (Pre_ab_return) and the abnormal turnover (Ab_turnover_stock, Ab_urinover_call and Ab_turnover_Put, respectively). Regressions 4 and 5 use the same independent variables, but the dependent variable is different. For Regression 4, it is the residual from regressing the post-announcement abnormal return on the pre-announcement abnormal return; for Regression 5, it is the residual from regressing the post-announcement abnormal return on the pre-announcement abnormal turnover. To enhance testing power, we first aggregate the observations into 100 equal groups by first sorting the abnormal turnover in question and then calculating the associated average abnormal turnover and abnormal returns for each group. The regressions are performed on the 100 groups. See the notes of Table 8 for details on the definition of event periods and abnormal turnover / returns. For each entry in the table, the upper number is the regression coefficient and the lower number the *t*-value. Significance levels of 10%, 5% and 1% are indicated by *, **, and *** respectively. For ease of presentation, all regression coefficients are multiplied by 100.

	Stocks					Call options					Put options				
	Dependent variable: post-annoucement abnormal return			Dependent variable: return residual		Dependent variable: post-annoucement abnormal return			Dependent variable: return residual		Dependent variable: post-annoucement abnormal return			Dependent variable: return residual	
Independent variable	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Intercept	6.413	3.109	3.531	-2.528	0.228	6.101	5.713	6.349	0.037	0.080	6.514	6.542	6.513	-0.0011	0.2041
	8.344 ***	4.421 ***	4.921 ***	-3.619 ***	0.375	10.141 ***	9.168 ***	9.872 ***	0.062	0.131	9.942 ***	8.897 ***	9.841 ***	-0.002	0.292
Pre_ab_return	34.622		18.825		17.763	16.329		24.448		6.296	49.517		49.664		21.697
	3.252 ***		2.163 **		2.109 **	3.705 ***		2.817 ***		1.395	7.316 ***		4.825 ***		3.003 ***
Ab_turnover_stock		25.968	24.332	22.959											
		8.241 ***	7.640 ***	7.336 ***											
Ab_turnover_call							0.833	-0.674	-0.173						
							2.555 **	-1.086	-0.551						
Ab_turnover_put												-1.844	0.010	0.004	
												-4.904 ***	0.019	0.013	
Adjusted R^2 (%)	8.82	40.33	42.49	34.79	3.36	11.39	5.29	11.55	-0.71	0.95	35.37	19.36	34.68	-1.05	7.71

Table 10: Predictive power of open-buy put-call ratio

In this table we investigate whether the open-buy put-call ratio predicts next day's returns. Following Pan and Poteshman (2006), we calculate the open-buy put-call ratio as the put volume divided by the sum of put and call volumes, all originated from buy-to-open transactions. The CBOE's Open/Close data for the period of January 1, 2006 to July 31, 2006 are used for this purpose. We run two sets of cross-section regressions: OLS and simultaneous regressions. OLS Regressions 1, 2, 3 and 4 replicate the results in Pan and Poteshman (2006, Table 4). Here we use today's put-call ratio to predict, in cross-section, tomorrow's four-factor risk-adjusted return. We then average the time-series of coefficients (the upper number in each entry) and calculate *t*-values (the lower number in each entry) with the Newey-West adjustment. As in Pan and Poteshman (2006), the stock turnover and spread are contemporaneous with the stock return. R(-5, -1) is the risk-adjusted, past five-day return. In the remaining OLS regressions, we add other variables: the current and lagged risk-adjusted returns, R(0), R(-1), R(-2), the current and lagged order imbalances, OIMB(0), OIMB(-1), OIMB(-2), OIMB(-3), OIMB(-4), firm size in logarithm, LnSize, and interactions between size and order imbalances. The regressions are also predictive in that the dependent variable is R(1), the one-day lead return. The last three columns report results for the simultaneous regressions specified in the text whereby we allow the put-call ratio (PC_ratio), the order imbalance (OIMB) and the risk-adjusted return (R) to be endogenous. The system is run following the three-stage least squares procedure. For efficiency, we augment the instrumental-variable set with three additional lags for each of the endogenous variables. Significance levels of 10%, 5% and 1% are indicated by *, **, and *** respectively. For ease of presentation, all regression coefficients involving the firm size are multiplied by 1000.

Explanatory	OLS regressions								Simultaneous regressions		
Variable	1	2	3	4	5	6	7	8	PC_Ratio	OIMB	R
Put-call ratio (0)	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	0.011	-0.002		0.001	-0.005
	-3.395 ***	-3.411 ***	-3.285 ***	-3.031 ***	-0.732	-0.742	1.061	-0.733		0.039	-1.181
Put-call ratio (-1)									0.276	0.003	0.000
									30.300 ***	0.602	0.163
Put-call ratio (-2)									0.229	-0.001	0.002
									24.778 ***	-0.213	1.650 *
Turnover		-0.003		-0.003							
		-0.559		-0.532							
Spread		0.448		0.428							
		1.065		1.050							
R(0)					-0.017	-0.018	-0.084	-0.018	-1.339	1.254	
					-0.448	-0.471	-1.812 *	-0.477	-1.414	3.944 ***	
R(-1)					0.005	0.005		0.005	-0.073	0.105	-0.041
					0.211	0.214		0.203	-0.405	1.703 *	-3.339 ***
R(-2)					0.007	0.007		0.006	0.349	-0.005	-0.024
					0.262	0.269		0.260	2.474 **	-0.135	-2.004 **
R(-5,-1)			-0.015	-0.016							
			-4.898 ***	-5.234 ***							
OIMB(0)					0.004	0.022	0.018	0.017	0.203		0.050
					0.719	1.463	1.059	1.094	1.314		2.946 ***
OIMB(-1)					-0.001	-0.020	-0.002	-0.017	-1.108	0.272	-0.012
					-0.696	-1.311	-0.061	-1.017	-2.914 ***	26.910 ***	-2.611 ***
OIMB(-2)					0.000	0.000	0.021	0.002	0.064	0.152	-0.007
					0.450	-0.017	0.770	0.173	0.148	14.190 ***	-2.107 **
OIMB(-3)					-0.001	-0.003	0.002	0.000	-0.576	0.159	-0.011
					-1.013	-0.179	0.133	-0.022	-1.191	14.415 ***	-2.749 ***
OIMB(-4)					-0.001	0.016	0.018	0.017	-0.129	0.125	-0.005
					-0.537	1.166	1.206	1.180	-0.297	10.599 ***	-1.239
LnSize							0.014	0.028	-8.692		
							0.163	0.326	-5.140 ***		
OIMB(0)*LnSize						-0.807	-0.511	-0.591	-10.298		
						-1.354	-0.832	-0.938	-1.281		
OIMB(-1)*LnSize						0.836	0.757	0.724	48.671		
						1.262	0.999	0.969	2.979 ***		
OIMB(-2)*LnSize						0.042	-0.110	-0.066	-1.882		
						0.075	-0.194	-0.116	-0.099		
OIMB(-3)*LnSize						0.082	-0.117	-0.022	26.867		
						0.122	-0.163	-0.031	1.295		
OIMB(-4)*LnSize						-0.766	-0.843	-0.809	4.330		
						-1.259	-1.290	-1.271	0.227		

Figure 1: Option trading around earnings announcements

The set of figures depict the trading activities of call and put options around quarterly earnings announcements broken down by trade type, size and type of trade initiator. The CBOE's Open/Close data for the period of January 1, 2006 to July 31, 2006 are used. The dataset reports, on a daily frequency, the breakdown of trading volumes for each option by trade type (buy/ sell/open/close), trade size (small/medium/large) and initiator (firm/customers). "Firm" stands for proprietary trading by brokerage firms on their own accounts while "customers" stands for all other trading except for market makers (a "customer" can be a retail investor or an institutional investor who uses the service of a brokerage firm). The size of trade for customers (in the number of contracts) is defined as small < 100, 100 ≤ medium ≤ 199 and large ≥ 200. To produce the plots, we first calculate the average proportion of each type/size/initiator combination relative to the total volume in the control period which is [-42, -23]. We then calculate the abnormal proportions for each day around the earnings announcement by subtracting the corresponding proportion in the control period. Day 0 corresponds to the announcement day. Each plot is for a particular transaction type, depending on whether it is for calls or puts and whether it is for opening or closing a position. The legends signify the 16 combinations of trade type, size and initiator for call and put. The first letter in the legend signifies either customers (C) or firms (F); the second letter indicates open (O) or close (C); the third letter indicates buy (B) or sell (S); and the subscript indicates the size (SM: small, MD: medium, or LG: large).

Figure 1A: Position-opening transactions for calls

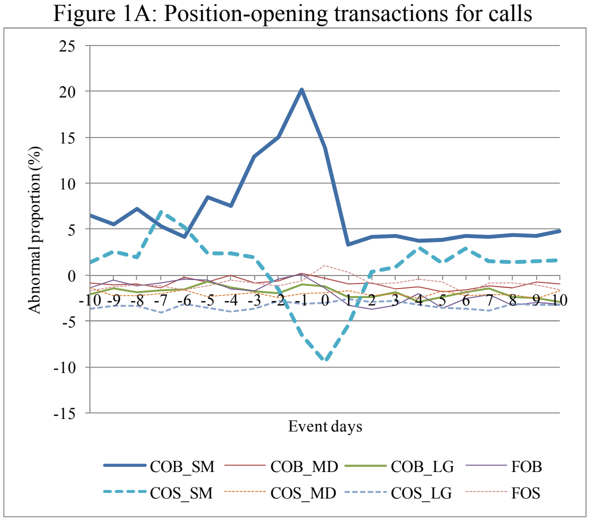


Figure 1B: Position-closing transactions for calls

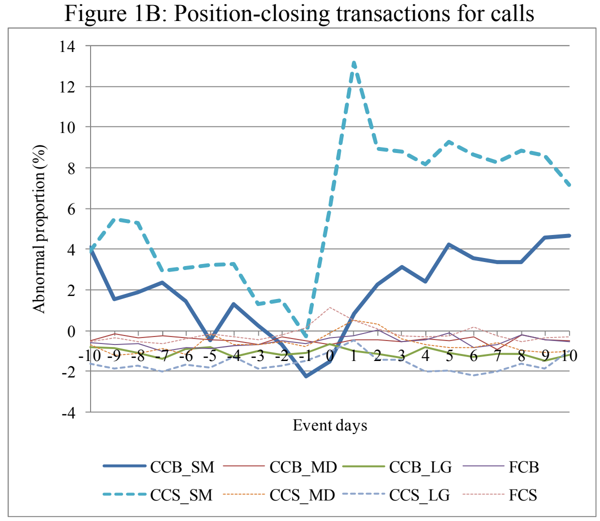


Figure 1C: Position-opening transactions for puts

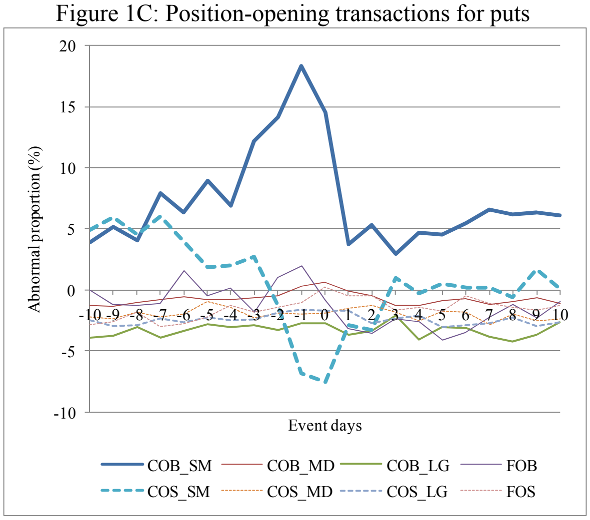
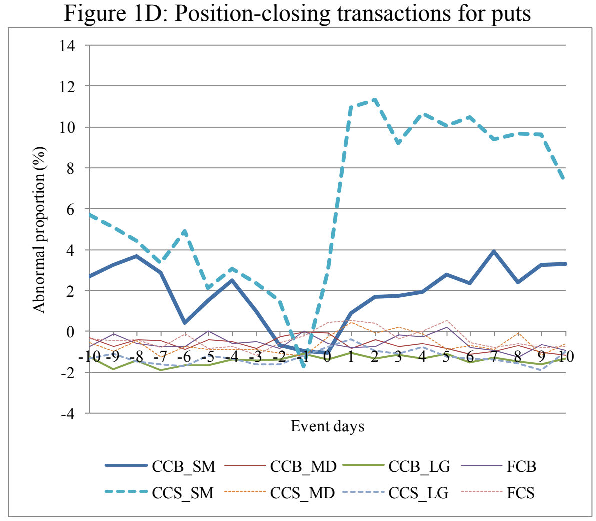


Figure 1D: Position-closing transactions for puts



Appendix: Definition of variables used in regression analysis

Note: The prefix "A" in each variable's name indicates that the variable is detrended. For example, "Alog_price" stands for the detrended, logarithm of stock price. All variables are aggregated to the weekly frequency by simple averaging of daily observations.

Dependent variables

Alog_stock_turnover: logarithm of stock turnover: $ln\left(0.001 + 100 \times \frac{trading\ volume}{shares\ outstanding}\right)$.

Alog_option_turnover: logarithm of option turnover: $ln\left(0.001 + 100 \times \frac{1}{n}\sum_{j=1}^{n}\frac{trading\ volume_j}{open\ interest_j}\right)$ where n is the total number of distinct call and put contracts in terms of maturity and moneyness. Similar turnover can be defined for calls and puts separately.

Alog_scaled_ratio: logarithm of volume ratio between option trading and stock trading. Specifically, for stock i on day t, the variable is defined as $ln\left(0.001 + \frac{scale_i \times option_volume_{i,t}}{scale_i \times option_volume_{i,t} + stock_volume_{i,t}}\right)$where option volume refers to the total daily volume of all options and $scale_i$ is the the total stock volume divided by the total option volume over the entire sample for stock i. The scale variable brings the trading volumes of stocks and options to comparable magnitudes.

Independent variables

Alog_price: logarithm of stock price.

Alog_size: logarithm of firm size calculated as stock price times the number of shares outstanding.

APIN: PIN (probability of informed trading, quarterly frequency).

Astock_pba: proportional bid-ask spread for stocks, calculated as the dollar bid-ask spread divided by the mid-point of bid and ask quotes.

Aoption_pba: proportional bid-ask spread for options, calculated as the dollar bid-ask spread divided by the mid-point of bid and ask quotes.

Alog_num_analyst: logarithm of one plus the number of analysts following the firm.

Asidedness: sidedness as defined in Sarkar and Schwartz (2009). In this paper, it is estimated as the correlation between the numbers of buyer- and seller-initiated trades over 5-minute intervals within the day.

ADISP: dispersion of earnings forecasts – standard deviation of earnings forecasts measured in dollars per share.

Ascaled_DISP: dispersion of earnings forecasts scaled by the average stock price within the calendar year of the estimates.

|Ascaled_change_DISP|: absolute value of the change in Ascaled_DISP.

Avolatility: return squared.

Return_positive: return of the week if positive and zero otherwise.

Return_negative: return of the week if negative and zero otherwise.