The Informational Role of Stock and Option Volume

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Abstract

This paper analyzes the intraday interdependence of order flows and price movements for actively traded NYSE stocks and their CBOE-traded options. Stock net-trade volume (buyer-initiated volume minus seller-initiated volume) has strong predictive ability for stock and option quote revisions, but option net-trade volume has no incremental predictive ability. This suggests that informed investors initiate trades in the stock market but not in the option market. On the other hand, both stock and option quote revisions have predictive ability for each other. Thus, while information in the stock market is contained in both quote revisions and trades, information in the option market is contained only in quote revisions. We also find some evidence of inventory control in both markets.

Introduction

In complete markets, option trading should convey no new information to market participants because options are derivative securities. In the absence of market completeness, however, informed traders may prefer to trade options instead of the underlying stocks for a couple of reasons. First, lower transaction costs and greater financial leverage may induce informed traders to trade in the option market instead of the stock market (Black (1975) and Mayhew, Sarin, and Shastri (1995)). Second, investors who have private information about volatility of the underlying stock price can only make their bet on volatility in the option market (Back (1993) and Cherian (1993)). For these reasons, the option market may not be redundant, and therefore can play an important role in discovering the information. On the other hand, lower liquidity of the option market may discourage informed traders from trading options. Easley, O'Hara, and Srinivas (1998, hereafter, EOS) characterize this scenario as a separating equilibrium where only uninformed traders transact in the option market while all informed traders transact in the liquid, stock market. In this case, option trading conveys little information.

Although numerous empirical studies address this issue and investigate the informational linkage between the stock market and the option market, there is no conclusive evidence as to where the informed investors trade and which market plays a greater role in discovering information. Based on intraday transaction data, Stephan and Whaley (1990) find that stock price movements lead option price movements. However, Chan, Chung, and Johnson (1993) caution that the stock lead documented in Stephan and Whaley (1990) could be due to price discreteness in the option market. They show that the stock lead disappears when the bid and ask quotes are used instead of transaction prices. Vijh (1990) finds that the price effects of large option trades are generally small, suggesting that option trades are not information-related. In contrast, EOS find that option trades have some predictive power for stock price changes.

In this paper we provide a comprehensive analysis of the interrelationship between the stock and option markets. We examine the dynamics of trades and quote revisions for actively traded New York Stock Exchange (NYSE) stocks and their Chicago Board Options Exchange (CBOE)-traded options. In particular, we investigate whether trades and quote returns in each of the two markets have any predictive ability for subsequent trades and quote returns in both markets.

We see several areas that our analysis adds to the literature. First, we expand the empirical literature on the informational linkage between the option and stock markets by integrating quote returns and trades into analysis. Most of previous studies examine the relationship either between price movements or between the trading activities in the two markets. For example, Manaster and Rendleman (1982) and Bhattacharya (1987) investigate the relationship between daily stock and option price changes while Anthony (1988) examines the linkage between the daily trading volume in the two markets. Although Stephan and Whaley (1990) investigate both price changes and volume in the two markets, they analyze the price change relationship and the volume relationship separately. By examining both quote revisions and trades together, this paper presents a more comprehensive study of the informational linkage between the two markets because quote revisions might contain information that is not contained in trades. For example, suppose that informed investors trade in the option market. It is possible that they submit either market orders or limit orders for trading on their private information. If they submit market orders in the option market, the direction of option trades (i.e., whether it is buyer-initiated or seller-initiated) will contain information. If they instead submit limit orders in the option market and cause the market quotes to change, their information will be incorporated into the option quote revisions. In other words, either the direction of option trades or option quote revisions can have predictive ability for quote revisions in the stock market.

Second, unlike those previous studies (Anthony (1988) and Stephan and Whaley (1990)) that use total trading volume, we make use of net-trade volume (buyer-initiated volume minus seller-initiated volume) to represent order flows. Net-trade volume, which measures temporary order imbalance, should provide information to the market makers for quote revisions. In many asymmetric information models (e.g., Kyle (1985) and Admati and Pfleiderer (1988)), market makers cannot distinguish whether a specific buy or sell order is from an informed trader or a liquidity trader, and therefore a rational pricing strategy for them is to revise the quotes upward (downward) when the net-trade volume is positive (negative). Such behavior is supported by empirical studies in the market microstructure literature (e.g., Glosten and Harris (1988), Hasbrouck (1991), Madhavan, Richardson, and Roomans (1997), and Huang and Stoll (1997)). These studies find that trade indicator variables (such as buyer-initiated and seller-initiated trades) are successful in explaining subsequent quote movements. Thus, if the stock market is a venue for informed trading, its net-trade volume should have predictive power for stock quote movements as well as option quote movements. Similarly, if the option market is a venue for informed trading, its net-trade volume should have predictive power for both option returns and stock returns.

This paper is not, of course, the first one that documents the impact of order flows on price movements in the stock and option markets. Vijh (1990), for example, investigates the price effect in the option market at the time of large option trades. He finds that there is little price effect and suggests that what many option traders consider to be superior information may be just a different opinion. Aggregating option trades into positive-news volume (buying a call or selling a put) and negative-news volume (selling a call or buying a put), EOS examine whether option trades are informative. They conclude that option trades are information-related and have predictive power for stock price changes. However, both Vijh (1990) and EOS examine the information content of option trades only. This paper extends their work by also including stock trades into analysis. As the current literature provides well-documented evidence that intraday stock trading volume leads intraday option trading volume more than it lags (e.g., Stephan and Whaley (1990)), it is possible that the information empirically inferred from option trades actually originates from stock trades.

This paper is organized as follows. Section I discusses the relationship among trades and quote revisions in the stock and option markets. Section II develops the empirical methodology for investigating the relationship and derives empirical predictions. Section III describes the data and provides summary statistics. Section IV presents the empirical results while Section V concludes the paper.

I. Trades and Quote Revisions in the Stock and Option Markets

In this section, we will discuss the interrelationship among the trades and quote revisions in the stock and option markets. First, we will discuss how the interrelationship may result from information effects, inventory control effects, and hedging effects. Based on the discussion, we could then motivate the empirical specifications, and make some empirical predictions about how trades and quote revisions in the two markets could be interrelated.

A. Information Effects

Although a number of studies (e.g., Black (1975) and Diamond and Verrecchia (1987)) suggest that informed investors prefer to trade in the option market, other research suggests that the market choice of informed investors in the stock and option markets is not straightforward.[1] EOS argue that the market choice of informed traders depends on the depth of the two markets as well as the leverage provided by the two markets. In particular, they show that two types of equilibria could exist. In a "separating equilibrium", informed traders trade in the stock market only. In a "pooling equilibrium", informed traders trade in both the stock and option markets, and therefore option trading could convey information about future stock price movements. For example, buying a call or selling a put conveys positive news about future stock prices, while selling a call or buying a put carries negative news. Furthermore, EOS find that positive-news option trades and negative-news option trades indeed have some predictive power for stock price movements.

In practice, informed investors could submit either market orders or limit orders to take advantage of their private information.[2] Informed traders may prefer to submit market orders which can be executed immediately and before their private information is learned by other investors. However, by submitting

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[1] John, Koticha, and Subrahmanyam (1993) suggest that informed trading in the option market may lead to an adverse selection problem, causing market makers to set larger bid-ask spread, thereby offsetting the benefit of leverage provided by the option market. In equilibrium, informed trading is split between the stock and option markets, with the proportion determined by liquidity trading and margin requirement in each market and the underlying volatility of the stock.

market orders they have to pay the bid-ask spread. Therefore, if the value of private information is less than the bid-ask spread, informed investors would either not trade or submit limit orders instead. This can be especially an important consideration in the option market, where the proportional bid-ask spread is relatively large (Vijh (1990)). Thus, even if informed investors trade in the option market, the way their information is being transmitted from the option market to the stock market depends on their order placement strategies. If they submit market orders so that they initiate the trades, option trades will have predictive ability for quote revisions in the stock market. On the other hand, if informed investors submit limit orders in the option market, their information will be reflected in the public limit order book. On the CBOE, the public limit order book is handled by an order book official. According to the CBOE rules, these public limit orders have priority over all other orders. If the public limit order quotes are not improved by the market makers, they will become the market best quotes.[3] Therefore, the limit orders of informed investors can cause quote revisions, which can then have predictive ability for the stock market. However, this might not happen frequently, since limit orders can also be submitted by liquidity suppliers or uninformed traders. If limit orders are submitted primarily by liquidity suppliers, quote revisions will not be informative. For example, Berkman (1996) studies the role of limit orders as supplier of liquidity for the stock options on the European Options Exchange (EOE). The EOE has a similar market structure to that of the CBOE, as the best quotes on the market can come from public limit orders or from designated market makers. Using a sample of large limit orders, Berkman finds that these limit orders indeed supply liquidity to the market.

B. Inventory Control Effects

In setting the bid-ask quotes, dealers tend to change the position of the quotes relative to the "true value" in order to induce public transactions that would even out their inventory positions. In Ho and Stoll (1983) and Stoll (1989), bid and ask quotes are lowered after public sales in order to induce public

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[2] For discussions of tradeoffs between submitting market orders and limit orders, see Glosten (1994), Handa and

purchases and inhibit additional public sales, while bid and ask quotes are raised after public purchases. This results in negative serial correlation in quote returns and reversal of public transactions. Many studies, such as Huang and Stoll (1994 and 1997), find evidence consistent with the inventory control effects for the NYSE stocks.

Evidence of inventory control is less clear in the option market. The CBOE options are traded in a multiple-dealer market, and therefore the collective ability of dealers to carry inventory to absorb imbalances is much higher. The ability of any one dealer to move bid-ask quotes is limited because she faces competition from other dealers who may have smaller inventories. Consistent with this notion, Vijh (1990) finds that the CBOE option market can absorb large orders with little change in price, although the dealers have to set wider bid-ask spreads to cover higher inventory costs. However, Berkman (1996) finds evidence of inventory control in the EOE. He shows that after transactions where market makers supply liquidity, quotes tend to return to their pre-trade level.[4]

C. Hedging Effects

If option dealers hedge their inventories using stock positions, such hedging behavior could create additional linkages between the stock and option markets (see EOS). According to Vijh (1990), option investors are more likely to be buyers rather than sellers, and therefore option dealers are more likely to be writers of the call and put options. To hedge their short call (put) positions, option dealers could buy (sell) stocks. Therefore, subsequent to public purchases of calls (puts), there could be an increase in purchases (sales) of stocks due to option dealers' hedging behavior. Certainly, this hedging effect might be related to the information effect. If the initial trade in the option market is from an informed trader, then this hedging behavior will also help to transmit the information from the option market to the stock market.

Schwartz (1996), and Focuault (1999).

[3] See Cox and Rubinstein (1985) for details.

[4] Option dealers sometimes hedge their inventories using stock positions. Unless they can rebalance their positions continuously, they face an additional dimension of inventory risk as a result of the option's stochastic return volatility. Jameson and Wilhelm (1992) find that the inability to rebalance an option position continuously and the uncertainty

Lagged stock returns can also affect net-trade volume in the option market if investors use options to dynamically hedge their long positions in the stock market. Investors may either sell call options or buy put options to reduce the risk exposure of their long stock positions. When stock price changes, the deltas of the call and put options also change, so investors have to rebalance their option positions to maintain an optimal hedge.

We caution, however, that the hedging effect is probably small relative to the information and inventory control effects. Given that the markets are not frictionless, investors and option dealers will not be able to rebalance their positions frequently. Because our study is based on high-frequency data, it might be difficult for us to detect hedging effects.

II. Methodology and Empirical Predictions

A. VAR Structure for Multiple Markets

We follow Hasbrouck (1991) in modeling the dynamic relationship among trades and quote revisions in the stock, call, and put markets. Hasbrouck proposes a bivariate VAR model of the trades and quote revisions for the stock market to measure the information content of stock trades. We extend his model to multiple markets so that we could examine the information content of stock trades and option trades together. We first explain a bivariate VAR model for a single market (e.g., the stock market):

$$r_t = a_1 r_{t-1} \,\ldots\ldots + a_p r_{t-p} + b_0 z_t + b_1 z_{t-1} \,\ldots\ldots + b_p z_{t-p} + \varepsilon_{1,t} \tag{1}$$

$$z_t = c_1 r_{t-1} \,\ldots\ldots + c_p r_{t-p} + d_1 z_{t-1} \,\ldots\ldots + d_p z_{t-p} + \varepsilon_{2,t} \tag{2}$$

where r_t is the quote return at transaction time t, which is the change in bid-ask midpoint from the quotes following transaction t-1 to the quotes following transaction t, and z_t is the signed volume (positive if buyer-initiated, negative if seller-initiated) of transaction t. It is assumed that the disturbances in the two equations have zero means and are jointly and serially uncorrelated.

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about the return volatility of the underlying stock account for a significant portion of the bid-ask spreads quoted for the CBOE options.

The above system is very similar to the usual VAR specification except that the contemporaneous signed volume appears as one of the explanatory variables in equation (1). In other words, there is a presumption of causality running from both contemporaneous and lagged trades to quote revisions, but from only lagged quote revisions to trades. Hasbrouck (1991) provides an excellent discussion of the superiority of this analysis over other plausible alternatives.

To extend equations (1) and (2) to multiple markets, define $\mathbf{r_t} = [r_t^s, r_t^c, r_t^p]'$ and $\mathbf{z_t} = [z_t^s, z_t^c, z_t^p]'$, where r_t^s, r_t^c and r_t^p represent quote returns in the stock, call, and put markets during time interval t, and z_t^s, z_t^c and z_t^p represent net-trade volume in the respective markets during time interval t. Our multivariate VAR model is as follows:

$$\mathbf{r_t} = \mathbf{a_1 r_{t-1}} \;\ldots\ldots + \mathbf{a_p r_{t-p}} + \mathbf{b_0 z_t} + \mathbf{b_1 z_{t-1}} \;\ldots\ldots + \mathbf{b_p z_{t-p}} + \boldsymbol{\varepsilon}_{\mathbf{1},\mathbf{t}} \tag{3}$$

$$\mathbf{z_t} = \mathbf{c_1 r_{t-1}} \;\ldots\ldots\ldots + \mathbf{c_p r_{t-p}} + \mathbf{d_1 z_{t-1}} + \ldots\ldots + \mathbf{d_p z_{t-p}} + \boldsymbol{\varepsilon}_{\mathbf{2},\mathbf{t}} \tag{4}$$

where $\mathbf{a_1}, \ldots\ldots, \mathbf{a_p}, \mathbf{b_0}, \mathbf{b_1}, \ldots\ldots, \mathbf{b_p}$, $\mathbf{c_1}, \ldots\ldots, \mathbf{c_p}, \mathbf{d_1}, \ldots\ldots, \mathbf{d_p}$ are (3x3) matrices of coefficients, while $\boldsymbol{\varepsilon}_{\mathbf{1},\mathbf{t}}$ and $\boldsymbol{\varepsilon}_{\mathbf{2},\mathbf{t}}$ are (3x1) vectors of disturbance terms. Instead of the system of two regression equations in Hasbrouck (1991), we now have a system of six regression equations. This structure suits our analysis as we could see, for example, whether trades in the call market still contain information and lead to stock and option quote revisions after controlling for trades in the stock and put markets and lagged quote revisions in all the three markets.

Our model is very similar in spirit to Hasbrouck's, yet there are two notable differences. First, ours is based on the calendar clock, as opposed to the transaction clock in Hasbrouck's. This is because Hasbrouck is interested in the dynamic behavior of trades and quote revisions in one market, but we are interested in the behavior in multiple markets. We therefore need to align different markets based on the calendar clock. Second, while Hasbrouck defines z_t as the signed volume of the trade at (transaction) time t, we define z_t as the net-trade volume during (calendar) time interval t. The reason is that we use the calendar clock and have to depend on the net aggregate of the signed volume of all trades in each time interval.

B. Empirical Predictions

B.1. Impacts of net-trade volume on returns

The impacts of net-trade volume on returns might come from the information effects and the inventory control effects. There are a few predictions from the information effects. In a "separating equilibrium" of EOS, where informed investors trade in the stock market, positive (negative) stock net-trade volume signals favorable (unfavorable) news and will be accompanied by upward (downward) revisions of the stock and call quotes and downward (upward) revisions of the put quotes. Therefore, stock net-trade volume is positively related to the contemporaneous and subsequent stock and call returns, but negatively related to the contemporaneous and subsequent put returns. In a "pooling equilibrium", where informed traders trade in both the stock and option markets, option net-trade volume will also have an impact on stock and option quote revisions. Positive (negative) call net-trade volume signals favorable (unfavorable) news while positive (negative) put net-trade volume signals unfavorable (favorable) news. Therefore call (put) net-trade volume is positively (negatively) related to the contemporaneous and subsequent stock and call returns, but negatively (positively) related to the contemporaneous and subsequent put returns.

As for the inventory control effects, market makers will revise quotes upward (downward) following an increase (a decrease) in net-trade volume in order to encourage offsetting orders. This however predicts that net-trade volume affects the contemporaneous and subsequent returns in its own market only, but not returns in the other markets.

B.2. Relationship among returns

The inventory control models predict negative serial correlation in quote returns in individual markets. On the other hand, the lead-lag relationship between returns in the stock and option markets stems mainly from the information effects. Furthermore, since the lead-lag relationship is after controlling for the explanatory power of net-trade volume in both markets, the information contained in quote revisions is in addition to that contained in stock and option trades. It might well be the case that informed investors in either the stock or option market sometimes submit limit orders to exploit their private information, and consequently their private information is first reflected in quote revisions and not in trades. If informed investors submit limit orders in the stock market only, stock returns will have predictive ability for subsequent option returns and not vice versa. On the other hand, if informed investors submit limit orders in both the stock and option markets, stock and option returns will have predictive ability for each other.

B.3. Impacts of returns on net-trade volume

Again, the inventory control models predict that net-trade volume is negatively related to the lagged quote revisions in its own market. On the other hand, hedging effects may also play some roles. If the stock price increases, the call delta increases and the put delta decreases in magnitude. Investors who use options to dynamically hedge their long positions in stocks may reduce their short call position (buy calls) or increase their long put position (buy puts). Thus, lagged stock returns may be positively related to subsequent call net-trade volume and put net-trade volume.

B.4. Relationship among net-trade volume

According to inventory control models, net-trade volume should have negative serial correlation. However, there is a counteracting force, as a large trader may work an order by distributing her purchases or sales over time (Hasbrouck and Ho (1987)). In that case, net-trade volume will have positive serial correlation.

There could be spillover across net-trade volume of different markets if option dealers hedge their inventories with stock positions. Since option dealers are more likely to be writers of the options, they need to buy (sell) stocks in order to hedge their short call (put) positions. Consequently, net-trade volume in the stock market is positively (negatively) related to lagged net-trade volume in the calls (puts).

III. Data and Preliminary Analysis

A. Sample

The data are retrieved from two sources. The first is the Berkeley Options Database, which contains a complete time-stamped history of quotes and trade prices of the options traded on the CBOE. The second is the Trade and Quote (TAQ) database of the NYSE, which contains time-stamped data on all trades and quotes on the NYSE, AMEX, and NASDAQ. Both databases contain the time to the nearest second, the price and volume for each trade, and, for quotations, the time and the bid and ask quotes. We obtain data for the first quarter (58 trading days) of 1995.

We start with the sixty most actively traded stocks on the NYSE (based on average daily trading volume) that do not split during our sample period as stock splits tend to affect the trading activities of the stocks. Hasbrouck (1995) finds that the preponderance of the price discovery for NYSE stocks takes place on the NYSE rather than other stock exchanges, so the inclusion of stock trades and quotes that originate outside the NYSE might bias the estimation of the information content of stock trades and quote revisions. Thus, we exclude the stock trades and quotes that originate outside the NYSE. Each day the most active CBOE-traded call and put contracts are selected for each stock. When the most active contract has five days or less to maturity, we select the next most active contract to eliminate option expiration effects documented elsewhere. Thus, each stock has at most 58 option days (days on which a matching sample of stock and option data are available). Since we require volume measurements over short time intervals, we need to delete option days with thin trading to mitigate the biases that may be otherwise resulted. We therefore delete those option days with fewer than 20 trades for the stock, the call, or the put. Since the approach of an ex dividend can cause unusual activity in an option, we also eliminate the option days just before ex-dividend. We are left with 14 active stocks and a total of 231 option days. Thus, a lot of option days (and the associated stocks) are deleted, mainly for the thin trading problem.

For each stock or option trade, we determine whether it is buyer-initiated or seller-initiated. Similar to EOS, we use two approaches to infer such direction of a trade. The first approach compares the trade price with the prevailing bid/ask quotes. Following Lee and Ready (1991), we discard the quotes that are less than five seconds before the trade. Such deletion seems appropriate for stocks, as the evidence in Lee and Ready suggests. Since there is no prior study on the classification of option trades, it is difficult to judge the extent to which the Lee and Ready procedure is accurate in the determination of the direction of option trades. For the sake of the robustness issue, however, we repeat our later tests without discarding the option quotes that are less than five seconds before the trades. We find that the results are qualitatively similar. Furthermore, to avoid the stale quote problem, we use only quotes that are within thirty minutes of the trade; otherwise, we will use the second approach. In the first approach, the trade is classified as buyer (seller) initiated if the trade price occurs at the ask (bid). If the trade price lies within the spread, we follow Harris (1989) and record the trade as buyer (seller) initiated if the trade price is closer to the ask (bid). In the second approach, which we use only if we cannot determine the direction of a trade using the first approach, we employ tick test to compare the trade price with the preceding trade price(s). A trade is classified as buyer (seller) initiated if it occurs on an uptick (downtick) or a zero uptick (downtick). When a trade occurs on consecutive zero ticks, it is not classified.

B. Summary Statistics

Table 1 presents our final sample of the CBOE options and their NYSE-traded underlying stocks. We report the average daily volume for each stock, its most active call and put, and all of its calls and puts during the sample option days. The stock volume is based on the number of round lots of shares traded while option volume is based on the number of contracts traded, and each option contract is for one round lot of shares. The average daily volume of the stocks is generally larger than that of the options.[5] It is notable that the trading volume of the most active call and put accounts for 29% to 73% of the trading volume of all calls and puts. This suggests that the trading activities of the most active call and put are good representatives in the option market, and that options other than the most active ones are often thinly traded. Thus, our analyses initially focus on the most active calls and puts, but later check the robustness of results using all calls and puts.

The percentages of buyer-initiated and seller-initiated volume vary across the stocks and options. For example, there are buying pressure for the stock of Sears Roebuck during the sample option days, and selling pressure for the stock of Citicorp. Since not all trades are classified, the sum of the percentages of buyer-initiated and seller-initiated volume is less than unity.

Table 2 presents additional statistics of the stocks and the most active call and put options. The average daily volume is decomposed into the average daily number of trades and the average trade size. We can see that the main reason for the stocks' volume being larger than the options' is that the average daily numbers of trades of the stocks are much larger than those of the options. The quotation frequency, which is the percentage of 5-minute intervals having new quotes, is also higher for the stocks. The evidence is consistent with previous studies that the stock market enjoys higher liquidity than the option market. A possible implication is that if an informed investor wants to transact a large trade immediately, she might be better off trading in the stock market even though there is lower degree of financial leverage. We also report the moneyness and time to expiration of the options. The most actively traded options appear to be at the money and of shorter-term maturity.

IV. Empirical Results

A. Regression Results based on 5-minute Intervals

We partition each option day into seventy-eight successive 5-minute intervals when both the

[5] The average daily volume is calculated using the days included in the sample. Thus, Ford Motor was the most

CBOE and the NYSE are open (i.e., from 9:30 a.m. to 4:00 p.m. EST). For each of the stocks, the most active calls, and the most active puts, we generate 5-minute return series using the last bid and ask quotes. If no quote is available for an interval, meaning that there is no quote change, we will use quotes from the previous interval. The return is calculated as the log of the ratio of quote midpoints in successive intervals. We also calculate the net-trade volume for every 5-minute interval for the stocks and the most active options. We follow EOS and standardize return and net-trade volume variables to control for their cross-sectional variations across different stocks and options. Each option day we first calculate the mean and standard deviation for a variable. The variable is then standardized by subtracting the mean and dividing by the standard deviation. Such standardization allows us to pool the entire 231 option days for later analyses so as to increase the power of the tests.

Using the sample option days, we estimate the multivariate VAR model in equations (3) and (4). Since we pool all the sample option days and use standardized net-trade volume and returns, we can assume that the disturbances are homoskedastic. Furthermore, as we include lagged values of the dependent variables on right hand side to capture serial dependency effects, the disturbances are likely to be serially uncorrelated. Similar to Hasbrouck (1991), we assume that the disturbances in equation (3) are contemporaneously uncorrelated with the disturbances in equation (4), and they all have zero means. Although the disturbances within equation (3), i.e., the three regression equations explaining stock, call, and put returns, are likely to be contemporaneously correlated with one another, there is no efficiency gain from using the seemingly unrelated regression estimation because the three regression equations have the same set of explanatory variables. Thus, we estimate the six regression equations separately by the ordinary least square method. We choose the contemporaneous (if applicable) and six lags for each explanatory variable, as using more lags does not affect the results. The results are presented in Table 3.

A.1. Effects of net-trade volume on quote returns

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actively-traded stock in the nine days included in the sample, but it might not be as actively traded in the days

First, we find that stock returns are affected by stock net-trade volume. There is not only a strong contemporaneous effect, but also a significant impact from the previous 5-minute stock net-trade volume.[6] In contrast, there is only a weak relation between stock returns and contemporaneous and lagged option net-trade volume. Although the call and put net-trade volume appear to affect stock returns marginally at the contemporaneous level, the signs of the coefficients contradict what we expect from the information role of the call and put trades. Therefore, it appears that it is the stock trades, not the option trades, that convey new information to the stock market.

Second, option returns are affected mainly by stock net-trade volume rather than by option net-trade volume. The contemporaneous stock net-trade volume has a strong and significant impact on both call returns (a coefficient of 0.308 with a t-statistic of 43.98) and put returns (a coefficient of –0.291 with a t-statistic of –41.32). Furthermore, there is also a significant impact from the first lagged stock net-trade volume. Although the contemporaneous call and put net-trade volume appear to affect their own returns, the signs of the coefficients contradict what we expect from the information effects. On the other hand, in the equation for explaining call returns, the coefficient for call net-trade volume of the first lag is significantly positive. This evidence however is more consistent with the inventory control effects than with the informational role of call trades, since although the first-lagged call net-trade volume affects call returns, it has no effect on stock and put returns. Overall, our findings suggest that stock trades play a much more important role than option trades in conveying new information to both the stock and option markets.

A.2. Relationship among quote returns

First, the results indicate that even after controlling for net-trade volume, quote returns in one market have predictive ability for subsequent quote returns in the other markets. For example, for the

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excluded.

[6] We have more than fifteen thousand 5-minute intervals. As Lindley (1957) points out, lower significance should be required for large samples. All the tests in this paper use the 0.1 percent significance level as the rejection criterion, instead of conventional levels of significance.

equation explaining stock returns, the coefficient for the first-lagged call (put) returns is 0.055 with a t-statistic of 6.31 (-0.043 with a t-statistic of –5.1). The signs of the coefficients are consistent with the information effects.

In each of the three return equations, the coefficients relating returns to their own lags are significantly negative. For example, the coefficient for the first lag is -0.149 for stock returns, -0.236 for call returns, and -0.227 for put returns. These results are consistent with the prediction of inventory control models.

A.3. Effects of quote returns on net-trade volume

First, we find that the coefficients measuring the effect of first-lagged returns on own net-trade volume in the option market are negative (-0.089 for calls and -0.087 for puts) and significant. These results are again consistent with the prediction of inventory control models. In contrast, such inventory control effect appears to be smaller in the stock market. The coefficient that measures the effect of the first-lagged stock returns on own net-trade volume is -0.032, and is only marginally significant.

Second, we do not find any significant impact of lagged stock returns on net-trade volume in the option market. Results are therefore inconsistent with the hedging effects, where investors rebalance their option positions following changes in stock prices.

Third, we find that lagged option returns have significant impacts on stock net-trade volume. In the equation for explaining stock net-trade volume, the coefficient for call returns of the first lag is 0.049 (with a t-statistic of 4.73), while the coefficient for put returns of the first lag is -0.033 (with a t-statistic of -3.33). This evidence is a little bit puzzling. Even though quote revisions in the option market contain information, if the market makers in the stock market update stock quotes correspondingly, there is no profit opportunity for investors to submit trades based on the information inferred from the option quote revisions. One possible explanation is that option dealers hedge their outstanding short option positions in the stock market. When the price of the call increases (the delta usually also increases), option dealers, who are usually writers of the call, have to buy more stocks to hedge their outstanding short positions. Similarly, when the price of the put increases (the delta usually increases also, in magnitude), option dealers, writers of the put, have to sell more stocks for hedging.

A.4. Relationship among net-trade volume

The net-trade volume in the stocks, calls, and puts are all positively autocorrelated. This is consistent with the notion that a large trader may work his order by distributing purchases or sales over time. The three net-trade volume series are, however, not significantly cross-autocorrelated, suggesting the direction of trades between the stock market and the option market is independent. It does not appear that option dealers trade in the stock market to hedge against their new option inventory positions. If they did, there should have been a spillover of net-trade volume from the option market to the stock market.

B. Comparison with EOS

Since EOS also examine whether option trades have predictive power for stock price changes, we would like to compare our study with their study. Actually, our results are quite comparable to those of EOS. A major finding of EOS is that both positive-news option volume and negative-news option volume have predictive ability for stock price changes, although it should be cautioned that the predictive ability is only significant at the contemporaneous level. In our Table 3, we also find that the relationship between stock returns and call or put net-trade volume is only significant at the contemporaneous level. Furthermore, similar to the evidence in EOS, the direction of the relationship between stock returns and call or put net-trade volume is in contradiction to the informational role of option trades - EOS find that negative-news (positive-news) option volume is associated with an increase (a decrease) in stock price, while we find that an increase in call (put) net-trade volume is associated with a decrease (an increase) in stock price. Our Table 3 also shows that although the contemporaneous call and put net-trade volume appear to affect their own returns, the signs of the coefficients contradict what we expect from the information effects.

To further demonstrate that our results are comparable to those of EOS, we modify our analysis by replacing call and put net-trade volume with positive-news and negative-news option volume in the regression equations for explaining stock and option returns. The results are reported in Table 4. Similar to EOS, we find the puzzling relationship that negative-news (positive-news) option volume is positively (negatively) associated with stock returns, and that the relationship is the strongest at the contemporaneous level. There is also a related puzzle: negative-news (positive-news) option volume is positively (negatively) associated with call returns and is negatively (positively) associated with put returns.

C. *Analysis based on 100-second Intervals*

We now shed some light onto the above-mentioned puzzle. The analyses so far are based on 5-minute intervals. One of the assumptions in our model is that the contemporaneous relationship among net-trade volume and quote revisions in the stock and option markets reflects the causality from net-trade volume to quote revisions and not vice versa. However, within a 5-minute interval, the trades could occur before or after the quote revisions. Thus, it could well be that net-trade volume and quote revisions are spuriously affecting each other at the contemporaneous level. To verify the causation relationship between the two variables, we repeat our analysis with 100-second intervals. Note that a 5-minute interval will be decomposed into three 100-second intervals. Thus, the contemporaneous relation between two variables measured for 5-minute intervals can become relations of one lead, one contemporaneous, and one lag if 100-second intervals are used.

We therefore re-estimate our model in equations (3) and (4) based on 100-second intervals and incorporate the contemporaneous (if applicable) and 18 lags for the explanatory variables on the right hand side. Table 5 presents the results. A notable result is that unlike Table 3, call (put) net-trade volume now does not have a significantly negative (positive) impact on stock returns at the contemporaneous level. This suggests that the puzzling relation of call and put net-trade volume with stock returns at the contemporaneous level in Table 3 is sensitive to the choice of the length of time intervals and may not really reflect the causality from call or put net-trade volume to stock returns. An equally notable result is that call and put net-trade volume now do not affect their own returns at the contemporaneous level. In contrast, the first lagged call (put) returns have a strong negative impact on current call (put) net-trade volume, and the first lagged call (put) net-trade volume has a mild positive impact on current call (put) returns. This lead-lag relation between call (put) returns and call (put) net-trade volume is consistent with the prediction of the inventory control effects.[7] It seems that the negative contemporaneous relation between returns and net-trade volume within the call market or within the put market based on 5-minute intervals is a manifestation of the lead-lag relation based on 100-second intervals. In other words, the puzzling negative contemporaneous relation between call (put) net-trade volume and call (put) returns in Table 3 does not really reflect the causality from net-trade volume to returns.

D. Summary

Our results for the interrelationships among quote returns and net-trade volume in the stock and option markets can be summarized in a four-by-four matrix below. To simplify, we define option returns as call returns or negative put returns, and option net-trade volume as call net-trade volume or negative put net-trade volume. Thus, we have four variables – stock returns, option returns, stock net-trade volume, and option net-trade volume. They are listed in the vertical axis and horizontal axis as the dependent and explanatory variables respectively. The cells in the matrix describe the empirical relationships among them.

[7] Note that the first lagged call net-trade volume affects call returns only, but not stock and put returns, and the first lagged put net-trade volume affects put returns only, but not stock and call returns. Thus this evidence is more consistent with the inventory control models than with the informational role of call and put trades.

		Explanatory Variables (Contemporaneous terms (if applicable) + Lagged terms)			
		Stock Returns	*Option returns*	*Stock net-trade volume*	*Option net-trade volume*
Dependent Variables	*Stock Returns*	*Negative*	*Positive*	*Positive*	-
	Option Returns	*Positive*	*Negative*	*Positive*	*Positive*
	Stock net-trade volume	*Negative*	*Positive*	*Positive*	-
	Option net-trade volume	-	*Negative*	-	*Positive*

The shaded cells reflect the cross-market relationships between the stock and option markets. The cross-market interrelationships include: (i) the positive impact of stock net-trade volume on option returns, (ii) the positive impact of stock returns on option returns, (iii) the positive impact of option returns on stock returns, and (iv) the positive impact of option returns on stock net-trade volume. The first three findings [(i), (ii), and (iii)] are consistent with the information transmission between the two markets. What is interesting is that stock net-trade volume contains information while option net-trade volume does not (i.e., option net-trade volume has no impact on stock returns). At the same time, the fact that stock and option returns could affect each other suggests that quote revisions in both markets contain useful information beyond what net-trade volume provides.

The cross-market relationship (iv) is somewhat puzzling, although it may be consistent with a conjecture that option dealers hedge their outstanding short option positions in the stock market. However, the lack of evidence of the other possible cross-market relationships, such as the insignificant impact of stock returns on option net-trade volume or the insignificant impact of option net-trade volume on stock net-trade volume, suggests that the hedging effect is minimal. This is probably not surprising given that our study is based on high-frequency data. Since the markets are not frictionless, investors and option dealers will not be able to rebalance their positions frequently.

The non-shaded cells reflect the relationships within the stock market or the option market. The relationships include: (i) the negative autocorrelation of stock returns and option returns, (ii) the negative impact of returns on net-trade volume, (iii) the positive impact of net-trade volume on returns, and (iv) the positive autocorrelation of stock net-trade volume and option net-trade volume. The first three relationships [(i), (ii), and (iii)] are all consistent with the inventory control effects.[8] The fourth relationship is consistent with the argument that a large trader may work his order by distributing purchases or sales over time.

E. Robustness Tests

Overall, our evidence indicates that while both stock and option quote revisions contain information, only stock trades, not option trades, have information content. There is also some evidence for inventory control effects, but little evidence for hedging effects. Now, we discuss results from some robustness tests.

E.1. Analysis with non-standardized variables

Our analyses are based on standardized variables: on every option day each variable is standardized by subtracting the mean and dividing by the standard deviation. Since the option delta may vary considerably during the day, there is an issue whether we can assume the mean return on the option to be constant. Furthermore, because of standardization, it is difficult to interpret the economic importance of the information content of stock trades and option trades.

We therefore estimate equations (3) and (4) for each option day with non-standardized variables.[9] We calculate the cross-sectional means of the coefficient estimates from the entire 231 option days. To test

[8] The positive impact of net-trade volume on returns in the stock market, not the option market, is also consistent with the information effects.
[9] Since there are only seventy-eight successive 5-minute intervals, we only use the contemporaneous and three lags of the explanatory variables so that we have a reasonable sample size for each option day.

the significance of the mean coefficient estimates, we calculate Z-statistics based on the approach discussed in Warner, Watts, and Wruck (1988) and Chung, Van Ness, and Van Ness (1999).[10]

The results are reported in Table 6. Note that these results are qualitatively similar to those with standardized variables (Table 3). To measure the economic significance of stock (call or put) net-trade volume on stock and option prices, we calculate the expected cumulative stock and option quote revisions conditional on a stock (call or put) net-trade volume innovation. We find that a hundred round lots of stock net-trade volume on average results in 2.8 cents increase in the stock quotation midpoint, 1.4 cents increase in the call quotation midpoint, and 0.9 cent decrease in the put quotation midpoint. The impact of a call or put net-trade volume innovation on stock and option quote revisions is generally much smaller.

E.2. Analysis based on number of trades

Jones, Kaul, and Lipson (1994) show that price movements are related more to number of trades than to trading volume. Therefore, we repeat our analysis replacing our net-trade volume variable by a simple counter that increments by +1 for each buyer-initiated trade and by –1 for each seller-initiated trade. The results, which are not reported here, are qualitatively similar to Table 3.

E.3. Analysis dropping call and put returns

Since option returns can explain stock returns as seen in Tables 3, 5, and 6, one can argue that the predictive power of option trades for stock quote revisions might be subsumed by the predictive power of option returns. Thus, we re-estimate the equation for explaining stock returns by dropping call returns and put returns as the explanatory variables. The results, which are not reported here, show that the coefficients of call and put net-trade volume in explaining stock returns remain either insignificant or having the signs that contradict what we expect for the information role of call and put trades.

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[10] That is, each Z-statistic is obtained by adding individual regression *t*-statistics across option days and then dividing

E.4. Analysis with all the calls and puts

The analysis so far uses only the most active call and put in each of the 231 sample option days. It is possible that trades of the calls and puts other than the most active ones are information-motivated. To examine this possibility, we repeat equations (3) and (4) with the call and put net-trade volume calculated from all the call and put contracts traded on the sample option days.[11] The results of this analysis, which are not reported here, are similar to Table 3.

E.5. Analysis with different screening criteria for the sample

We select the most actively traded stocks and then select the most active option contracts for these stocks. One might argue that there is a selection bias because we select the most active stocks before we select the options: the stocks included in our sample are thus more likely to be information-related than the matching options. We think the bias is insignificant. It should be noted that the trading activities (in terms of total trading volume) of stocks and options are highly correlated. In fact, when we select the active option contracts first (based on daily total trading volume) and then match them with the stocks, the resulting sample is very similar to the sample in Table 1, confirming that there is no bias from our screening criteria.

E.6. Analysis controlling for volume intraday patterns

It is well known that volume on both stock and option markets reveal distinct U-shaped intraday patterns. To test whether these intraday patterns affect the results, we repeat equations (3) and (4) dropping the observations during 9:30-10:30 a.m. and 3:30-4:00 p.m. EST. The results, not reported here, are similar to Table 3.

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the sum by the square root of the number of option days.

[11] To generate the series for call (put) net-trade volume, we aggregate the net-trade volume across all calls (puts) for a stock. The call and put net-trade volume series are then standardized by subtracting the mean and dividing by the

V. Conclusion

This paper provides a comprehensive analysis of the interdependence of net-trade volume (buyer-initiated trading volume minus seller-initiated trading volume) and quote revisions for actively traded NYSE stocks and their CBOE-traded options. A distinct contribution is that we provide evidence on the price discovery roles of the two markets by examining the information respectively contained in the quote revisions and trades in each market.

Our results show that stock net-trade volume has strong predictive ability for contemporaneous and subsequent stock and option quote revisions, but option net-trade volume has no incremental predictive ability. This suggests that informed investors initiate trades in the stock market but not in the option market. On the other hand, option quote revisions, as well as stock quote revisions, have predictive ability for subsequent quote revisions in the other market. In other words, while information in the stock market is contained in both quote revisions and trades, information in the option market is contained only in quote revisions. We also find some evidence of inventory control in both markets (e.g., negative autocorrelation of quote revisions). We however find little evidence of hedging effects (e.g., stock returns do not appear to affect option net-trade volume). This is perhaps because we use high-frequency data in our study.

The evidence that option quote revisions, not option trades, contain some information is particularly interesting, yet a little bit puzzling. We conjecture that even though informed investors also trade in the option market, they do not initiate trades aggressively (i.e., do not submit market orders), so that option trades (whether buyer-initiated or seller-initiated) do not contain information. Instead, they would rather submit orders passively (i.e., limit orders) in the option market, hoping that some uninformed investors or liquidity traders would initiate trades with them. If their limit orders improve either the market bid or the market ask, there will be quote revisions. Thus, quote revisions would contain valuable information. Given the benefit of financial leverage associated with the options, it might be surprising that informed investors still hesitate to initiate option trades. One possible reason is the low liquidity in the

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standard deviation for each option day. Note that we still calculate the call and put returns based on the quotes of the option market. If the value of private information is not large, informed traders would not submit market orders in the option market to avoid incurring the relatively large bid-ask spread. For them to initiate trades in the option market, the benefit of immediacy has to be large enough. This might be one of the explanations why some recent work (e.g. Cao, Chen, and Griffin (1999)) show that option trades have information content around some firm-specific events, when the value of private information is probably large.

most active call and put.

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Table 1

Daily Trading Volume of Stocks, Calls, and Puts

Average daily trading volume of 14 actively traded NYSE stocks and their CBOE-traded options during sample days in the first quarter of 1995. For each stock, a trading day will be included in the sample when the stock, the most active call, and the most active put all have at least 20 trades for the day. The number of days included in the final sample is reported. The daily trading volume of the stock (call and put) is in terms of round lots (contracts). Buy (sell) volume is the buyer-initiated (seller-initiated) volume, and is expressed in terms of the percentage of the total trading volume. The trading volume of the most active call (put) is expressed in terms of the percentage of the total trading volume of all the calls (puts).

		Average Daily Stock Volume			Average Daily Call Volume				Average Daily Put Volume			
Firm Name	No. of days	Total Volume (in round lots)	Buy Volume (in %)	Sell Volume (in %)	All Calls (in contracts)	Most Active Call (in %)	Buy Volume (in %)	Sell Volume (in %)	All Puts (in contracts)	Most Active Put (in %)	Buy Volume (in %)	Sell Volume (in %)
Best Buy	9	9,246	42.3	41.3	1,500	33.0	41.6	42.4	2,526	45.8	43.3	47.4
Chrysler	24	28,350	33.3	41.7	5,471	35.0	45.9	45.8	2,063	48.2	40.7	43.1
Citicorp	12	27,007	31.2	41.3	1,911	45.9	46.7	44.6	2,250	47.4	43.7	49.4
Callaway Golf	5	14,374	41.3	42.7	2,139	31.9	42.1	46.2	1,777	38.9	50.8	43.9
EMC Corp	20	27,706	40.2	40.0	2,143	34.1	48.0	40.6	958	48.1	34.5	56.3
Ford Motor	9	34,730	38.5	43.2	2,130	36.3	48.8	30.8	659	56.8	38.2	52.0
General Electric	7	18,805	46.1	33.9	1,777	37.8	48.2	43.6	818	48.4	41.8	38.7
General Motor	32	24,587	38.1	34.1	3,890	36.8	42.7	43.4	1,589	40.7	37.6	42.8
Hewlett Packard	14	10,081	46.1	32.0	1,752	34.9	41.6	53.1	1,162	42.5	43.7	44.4
IBM	56	19,921	47.5	35.1	9,047	32.2	47.7	45.3	4,391	34.1	47.2	41.4
Merck	11	22,574	45.1	36.3	3,311	29.1	39.9	47.3	1,226	58.9	39.0	32.0
Micron Technology	11	27,160	42.8	36.4	1,746	42.1	48.7	41.0	2,054	39.5	44.7	47.0
Sears Roebuck	7	29,514	48.7	31.9	5,284	73.2	44.1	50.5	5,166	55.4	43.1	49.3
Texas Instruments	14	12,553	40.9	30.4	2,720	42.9	45.3	48.7	1,304	47.7	46.9	46.6
Simple Average	17	21,901	41.6	37.2	3,202	38.9	45.1	44.5	1,996	46.6	42.5	45.3

Table 2
Summary Statistics of Stocks, Calls, and Puts

Summary statistics of 14 actively traded NYSE stocks and their most active CBOE-traded options during sample days in the first quarter of 1995. For each stock, a trading day will be included in the sample when the stock, the most active call, and the most active put all have at least 20 trades for the day. The average trade size of the stock (call and put) equals average daily volume divided by average daily number of trades and is in terms of round lots (contracts). Quotation frequency denotes the percentage of 5-minute intervals having new quotes. For each option, the moneyness is calculated by dividing the average stock price in the day by the strike price, where the average stock price in the day is the mean of the midpoints of the prevailing bid and ask quotes at the end of the 5-minute intervals. For each stock, the minimum, mean, and maximum of the option moneyness and the options' average time to expiration during the sample days are reported.

	Stock			The Most Active Call					The Most Active Put				
Firm Name	Daily no. of trades	Average trade size (in round lots)	Quotation frequency (in %)	Daily no. of trades	Average trade size (in contracts)	Quotation frequency (in %)	Option moneyness	Time To expiration (in days)	Daily no. of trades	Average trade size (in contracts)	Quotation frequency (in %)	Option moneyness	Time to expiration (in days)
Best Buy	371	25	54	30	17	27	0.86,0.94,1.07	14	35	33	35	0.87,1.00,1.08	27
Chrysler	676	42	57	87	22	46	0.86,0.99,1.06	25	36	28	31	0.97,1.03,1.12	27
Citicorp	397	68	54	43	20	28	0.97,1.00,1.07	38	34	32	30	0.97,1.02,1.12	35
Callaway Golf	653	22	57	33	21	43	0.80,0.94,1.09	23	28	25	48	0.92,0.96,1.02	70
EMC Corp	509	54	42	46	16	29	0.89,0.98,1.14	46	30	15	26	0.91,1.00,1.14	34
Ford Motor	644	54	37	35	22	29	0.92,1.02,1.10	64	22	17	20	0.87,1.01,1.10	29
General Electric	923	20	51	41	16	30	0.97,0.99,1.00	22	26	15	30	0.99,1.01,1.07	48
General Motor	419	59	50	64	23	50	0.94,1.01,1.08	18	37	18	29	0.94,1.04,1.13	29
Hewlett Packard	502	20	85	35	18	58	0.96,1.00,1.04	18	31	16	44	1.00,1.03,1.06	18
IBM	615	32	69	156	19	60	0.93,0.99,1.03	21	82	18	54	0.97,1.02,1.07	26
Merck	579	39	38	54	18	34	0.93,1.01,1.09	35	29	25	15	1.00,1.04,1.09	45
Micron Technology	1,096	25	90	41	18	63	0.93,0.99,1.03	20	28	29	51	0.99,1.04,1.12	20
Sears Roebuck	508	58	61	50	77	27	0.94,0.97,1.04	33	38	75	22	1.01,1.05,1.08	20
Texas Instruments	442	28	85	63	18	61	0.94,1.01,1.09	20	32	20	48	0.99,1.02,1.11	24
Simple Average	595	39	59	56	23	42	0.92,0.99,1.07	28	35	26	35	0.96,1.02,1.09	32

Table 3
Regression Analysis of the Relationship Among Standardized 5-Minute Returns and Standardized 5-Minute Net-Trade Volume of Stocks, Calls, and Puts

The following multivariate VAR model is estimated:

$$\mathbf{r_t} = \mathbf{a_1 r_{t-1}} \ldots\ldots + \mathbf{a_p r_{t-p}} + \mathbf{b_0 z_t} + \mathbf{b_1 z_{t-1}} \ldots\ldots + \mathbf{b_p z_{t-p}} + \boldsymbol{\varepsilon}_{1,t}$$

$$\mathbf{z_t} = \mathbf{c_1 r_{t-1}} \ldots\ldots + \mathbf{c_p r_{t-p}} + \mathbf{d_1 z_{t-1}} + \ldots\ldots + \mathbf{d_p z_{t-p}} + \boldsymbol{\varepsilon}_{2,t}$$

where $\mathbf{r_t} = [r_t^s, r_t^c, r_t^p]'$, $\mathbf{z_t} = [z_t^s, z_t^c, z_t^p]'$, r_t^s, r_t^c and r_t^p represent quote returns in the stock, call, and put markets during 5-minute time interval t, and z_t^s, z_t^c and z_t^p represent net-trade volume (buyer-initiated volume minus seller-initiated volume) in the respective markets during time interval t. All return and net-trade volume series are standardized by subtracting the mean and dividing by the standard deviation of the day. We use the contemporaneous (if applicable) and six lags for the explanatory variables, and report the regression coefficients for the contemporaneous and first two lags (lags 3 through 6 are not shown to save space) and *t*-statistics (in *italics*) with * indicating significance at the 0.1 percent level.

	Explanatory Variables														
	Lagged Stock returns		*Lagged Call returns*		*Lagged Put returns*		*Lagged Stock net-trade volume*			*Lagged Call net-trade volume*			*Lagged Put net-trade volume*		
Dependent Variable	Lag 1	Lag 2	Lag 1	Lag 2	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2
Stock returns	-0.149	-0.088	0.055	0.014	-0.043	-0.008	0.415	0.080	0.023	-0.018	-0.002	0.001	0.026	-0.004	-0.004
	*-15.73**	*-8.79**	*6.31**	*1.54*	*-5.10**	*-0.99*	*61.91**	*10.49**	*2.95*	*-2.71*	*-0.28*	*0.18*	*3.88**	*-0.56*	*-0.63*
Call returns	0.237	0.154	-0.236	-0.157	-0.035	0.005	0.308	0.036	0.008	-0.035	0.031	0.010	0.019	-0.007	-0.001
	*23.95**	*14.60**	*-25.94**	*-16.68**	*-4.06**	*0.60*	*43.98**	*4.48**	*0.95*	*-4.97**	*4.44**	*1.38*	*2.71*	*-1.04*	*-0.10*
Put returns	-0.200	-0.132	-0.042	-0.003	-0.227	-0.150	-0.291	-0.032	0.002	0.030	0.002	-0.008	-0.049	0.016	0.015
	*-20.12**	*-12.48**	*-4.54**	*-0.31*	*-25.89**	*-16.64**	*-41.32**	*-3.99**	*0.20*	*4.30**	*0.32*	*-1.16*	*-6.96**	*2.26*	*2.15*
Stock net-trade volume	-0.032	0.017	0.049	0.010	-0.033	0.000		0.054	-0.017		-0.001	-0.002		0.011	-0.006
	-2.89	*1.46*	*4.73**	*0.90*	*-3.33**	*-0.05*		*6.03**	*-1.91*		*-0.07*	*-0.23*		*1.35*	*-0.81*
Call net-trade volume	-0.006	0.039	-0.089	-0.024	-0.006	-0.019		0.028	0.011		0.049	-0.013		0.002	0.006
	-0.56	*3.27*	*-8.52**	*-2.27*	*-0.57*	*-1.90*		*3.08*	*1.18*		*6.17**	*-1.68*		*0.25*	*0.78*
Put net-trade volume	-0.012	-0.005	0.010	0.005	-0.087	0.009		0.008	-0.006		0.002	0.010		0.069	0.003
	-1.08	*-0.43*	*0.93*	*0.45*	*-8.73**	*0.91*		*0.88*	*-0.65*		*0.28*	*1.30*		*8.77**	*0.32*

Table 4

Regression Analysis of the Relationship Among Standardized 5-minute Returns of Stocks, Calls, and Puts and Standardized 5-minute Stock Net-Trade Volume, Positive-News Option Volume, and Negative-News Option Volume

The following model is estimated:

$$\mathbf{r_t} = \mathbf{a_1 r_{t-1}} \;\ldots\ldots + \mathbf{a_p r_{t-p}} + \mathbf{b_0 z_t} + \mathbf{b_1 z_{t-1}} \;\ldots\ldots + \mathbf{b_p z_{t-p}} + \boldsymbol{\varepsilon}_{1,t}$$

where $\mathbf{r_t} = [r^s_t, r^c_t, r^p_t]'$, $\mathbf{z_t} = [z^s_t, z^c_t, z^p_t]'$, r^s_t, r^c_t and r^p_t represent quote returns in the stock, call, and put markets during 5-minute time interval t, z^s_t represents stock net-trade volume (buyer-initiated volume minus seller-initiated volume) during time interval t, z^c_t and z^p_t represent positive-news (buyer-initiated call volume plus seller-initiated put volume) and negative-news (seller-initiated call volume plus buyer-initiated put volume) option volume. All return and volume series are standardized by subtracting the mean and dividing by the standard deviation of the day. We use the contemporaneous (if applicable) and 6 lags for the explanatory variables, and report the regression coefficients for the contemporaneous and first two lags (lags 3 through 6 are not shown to save space) and *t*-statistics (in *italics*) with * indicating significance at the 0.1 percent level.

	Explanatory Variables														
	Lagged stock returns		*Lagged call returns*		*Lagged put returns*		*Lagged stock net-trade volume*			*Lagged positive-news option volume*			*Lagged negative-news option volume*		
Dependent Variable	Lag 1	Lag 2	Lag 1	Lag 2	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2
	Panel A: With lagged stock net-trade volume as explanatory variables														
Stock returns	-0.150	-0.089	0.055	0.015	-0.043	-0.008	0.415	0.080	0.022	-0.015	-0.001	-0.007	0.028	-0.001	-0.003
	*-15.81**	*-8.82**	*6.34**	*1.64*	*-5.19**	*-0.89*	*61.91**	*10.49**	*2.89*	*-2.27*	*-0.17*	*-1.06*	*4.18**	*-0.18*	*-0.41*
Call returns	0.236	0.153	-0.236	-0.157	-0.035	0.005	0.308	0.035	0.007	-0.009	0.015	0.001	0.047	-0.021	-0.006
	*23.85**	*14.54**	*-25.98**	*-16.76**	*-4.06**	*0.53*	*43.89**	*4.42**	*0.89*	*-1.32*	*2.19*	*0.11*	*6.62**	*-2.97*	*-0.81*
Put returns	-0.199	-0.133	-0.041	-0.003	-0.226	-0.151	-0.291	-0.032	0.003	0.028	0.004	-0.010	-0.046	0.010	0.009
	*-20.03**	*-12.54**	*-4.50**	*-0.33*	*-25.75**	*-16.83**	*-41.24**	*-4.01**	*0.32*	*3.98**	*0.61*	*-1.40*	*-6.54**	*1.37*	*1.27*
	Panel B: Without lagged stock net-trade volume as explanatory variables														
Stock returns	-0.126	-0.077	0.086	0.024	-0.069	-0.014				-0.014	-0.004	-0.003	0.039	-0.002	-0.001
	*-12.41**	*-7.13**	*8.87**	*2.37*	*-7.40**	*-1.46*				*-1.87*	*-0.56*	*-0.40*	*5.20**	*-0.29*	*-0.13*
Call returns	0.244	0.157	-0.216	-0.152	-0.052	0.002				-0.009	0.012	0.003	0.055	-0.022	-0.004
	*24.32**	*14.74**	*-22.54**	*-15.37**	*-5.63**	*0.19*				*-1.22*	*1.68*	*0.47*	*7.32**	*-2.92*	*-0.60*
Put returns	-0.205	-0.133	-0.060	-0.007	-0.210	-0.149				0.028	0.007	-0.012	-0.054	0.011	0.008
	*-20.48**	*-12.45**	*-6.29**	*-0.70*	*-22.92**	*-15.87**				*3.79**	*0.99*	*-1.64*	*-7.20**	*1.42*	*1.05*

Table 5
Regression Analysis of the Relationship Among Standardized 100-Second Returns and Standardized 100-Second Net-Trade Volume of Stocks, Calls, and Puts

The following multivariate VAR model is estimated:

$$\mathbf{r_t} = \mathbf{a_1 r_{t-1}} \; \ldots\ldots + \mathbf{a_p r_{t-p}} + \mathbf{b_0 z_t} + \mathbf{b_1 z_{t-1}} \; \ldots\ldots + \mathbf{b_p z_{t-p}} + \boldsymbol{\varepsilon}_{1,t}$$

$$\mathbf{z_t} = \mathbf{c_1 r_{t-1}} \; \ldots\ldots + \mathbf{c_p r_{t-p}} + \mathbf{d_1 z_{t-1}} + \ldots\ldots + \mathbf{d_p z_{t-p}} + \boldsymbol{\varepsilon}_{2,t}$$

where $\mathbf{r_t} = [r_t^s, r_t^c, r_t^p]'$, $\mathbf{z_t} = [z_t^s, z_t^c, z_t^p]'$, r_t^s, r_t^c and r_t^p represent quote returns in the stock, call, and put markets during 100-second time interval t, and z_t^s, z_t^c and z_t^p represent net-trade volume (buyer-initiated volume minus seller-initiated volume) in the respective markets during time interval t. All return and net-trade volume series are standardized by subtracting the mean and dividing by the standard deviation of the day. We use the contemporaneous (if applicable) and 18 lags for the explanatory variables, and report the regression coefficients for the contemporaneous and first two lags (lags 3 through 18 are not shown to save space) and *t*-statistics (in *italics*) with * indicating significance at the 0.1 percent level.

	Explanatory Variables														
	Lagged Stock returns		*Lagged Call returns*		*Lagged Put returns*		*Lagged Stock net-trade volume*			*Lagged Call net-trade volume*			*Lagged Put net-trade volume*		
Dependent Variable	Lag 1	Lag 2	Lag 1	Lag 2	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2
Stock returns	-0.099	-0.086	0.075	0.038	-0.033	-0.018	0.293	0.137	0.037	0.006	0.002	-0.003	0.007	-0.009	0.010
	*-20.22**	*-17.00**	*15.93**	*7.93**	*-7.18**	*-3.82**	*71.76**	*31.33**	*8.36**	*1.41*	*0.45*	*-0.82*	*1.72*	*-2.16*	*2.34*
Call returns	0.178	0.113	-0.169	-0.116	-0.037	-0.014	0.198	0.069	0.004	-0.005	0.024	0.006	0.007	-0.008	0.011
	*35.43**	*21.74**	*-35.07**	*-23.53**	*-7.78**	*-2.97*	*47.39**	*15.34**	*0.91*	*-1.27*	*5.69**	*1.54*	*1.68*	*-2.03*	*2.69*
Put returns	-0.155	-0.087	-0.052	-0.032	-0.164	-0.102	-0.166	-0.061	-0.004	0.008	0.000	0.007	-0.011	0.018	0.000
	*-30.69**	*-16.75**	*-10.71**	*-6.54**	*-34.39**	*-21.16**	*-39.64**	*-13.68**	*-0.93*	*1.84*	*-0.01*	*1.67*	*-2.73*	*4.43**	*-0.04*
Stock net-trade volume	-0.028	-0.022	0.041	0.022	-0.033	-0.024		0.059	0.018		-0.004	0.013		0.001	0.006
	*-5.07**	*-3.86**	*7.77**	*4.08**	*-6.39**	*-4.60**		*12.13**	*3.54**		*-0.80*	*2.89*		*0.11*	*1.28*
Call net-trade volume	-0.013	0.004	-0.081	-0.040	0.005	-0.004		0.009	0.011		0.070	0.023		-0.003	-0.004
	-2.34	*0.63*	*-15.22**	*-7.38**	*0.87*	*-0.77*		*1.77*	*2.27*		*15.36**	*5.09**		*-0.64*	*-0.80*
Put net-trade volume	0.004	0.004	-0.001	-0.002	-0.073	-0.058		0.001	0.000		-0.008	0.001		0.086	0.023
	0.63	*0.69*	*-0.18*	*-0.29*	*-13.92**	*-10.92**		*0.21*	*0.07*		*-1.66*	*0.21*		*18.75**	*5.04**

Table 6
Regression Analysis of the Relationship Among Non-Standardized 5-Minute Dollar Returns and Non-Standardized 5-Minute Net-Trade Volume of Stocks, Calls, and Puts

The following multivariate VAR model is estimated:

$$\mathbf{r_t} = \mathbf{a_1 r_{t-1}} \;\ldots\ldots + \mathbf{a_p r_{t-p}} + \mathbf{b_0 z_t} + \mathbf{b_1 z_{t-1}} \;\ldots\ldots + \mathbf{b_p z_{t-p}} + \boldsymbol{\varepsilon}_{1,t}$$

$$\mathbf{z_t} = \mathbf{c_1 r_{t-1}} \;\ldots\ldots + \mathbf{c_p r_{t-p}} + \mathbf{d_1 z_{t-1}} + \ldots\ldots + \mathbf{d_p z_{t-p}} + \boldsymbol{\varepsilon}_{2,t}$$

where $\mathbf{r_t} = [r_t^s, r_t^c, r_t^p]'$, $\mathbf{z_t} = [z_t^s, z_t^c, z_t^p]'$, r_t^s, r_t^c and r_t^p represent dollar returns in the stock, call, and put markets during 5-minute time interval t, and z_t^s, z_t^c and z_t^p represent net-trade volume (i.e., buyer-initiated volume minus seller-initiated volume) for the stock market (in hundred round lots), the call market (in hundred contracts), and the put market (in hundred contracts) during time interval t. Returns are computed with the mid-point of the bid and ask quotes at the end of each 5-minute interval. Regression is run separately for each option day. We use the contemporaneous (if applicable) and three lags for the explanatory variables, and report the cross-sectional mean regression coefficients for the contemporaneous and first two lags (lag 3 is not shown to save space) and Z-statistics (in *italics*) with * indicating significance at the 0.1 percent level.

	Explanatory Variables														
	Lagged Stock returns		*Lagged Call returns*		*Lagged Put returns*		*Lagged Stock net-trade volume*			*Lagged Call net-trade volume*			*Lagged Put net-trade volume*		
Dependent Variable	Lag 1	Lag 2	Lag 1	Lag 2	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2	Lag 0	Lag 1	Lag 2
Stock returns	-0.153	-0.103	0.137	0.035	-0.189	-0.013	0.0227	0.0021	-0.0004	-0.0047	0.0062	0.0013	0.0078	-0.0045	0.0006
	*-13.20**	*-8.59**	*6.59**	*2.03*	*-4.62**	*-0.07*	*57.10**	*8.15**	*1.19*	*-2.22*	*-0.30*	*-0.85*	*3.20*	*-0.15*	*0.00*
Call returns	0.144	0.088	-0.245	-0.163	-0.071	0.016	0.0094	0.0009	-0.0000	-0.0077	0.0052	0.0006	0.0046	-0.0055	0.0025
	*21.99**	*12.97**	*-22.02**	*-14.58**	*-4.17**	*0.78*	*41.26**	*3.81**	*-0.74*	*-4.78**	*3.47**	*1.00*	*2.24*	*-0.54*	*0.85*
Put returns	-0.109	-0.066	-0.037	-0.020	-0.241	-0.158	-0.0067	-0.0009	0.0003	0.0014	0.0004	0.0001	-0.0091	0.0019	0.0037
	*-17.33**	*-11.15**	*-3.55**	*-0.89*	*-22.12**	*-14.11**	*-37.72**	*-4.31**	*0.62*	*2.58*	*0.19*	*-1.34*	*-6.86**	*1.81*	*1.77*
Stock net-trade volume	-2.839	1.420	2.423	3.448	-1.050	1.829		0.079	-0.005		-0.610	0.111		0.074	0.079
	*-3.34**	*1.28*	*3.38**	*1.55*	*-2.22*	*0.19*		*7.47**	*-0.02*		*-0.55*	*0.41*		*0.79*	*-0.48*
Call net-trade volume	-0.210	-0.017	-0.900	0.277	-0.060	0.308		0.003	0.003		0.073	-0.019		0.020	0.051
	-1.30	*-0.10*	*-6.74**	*1.32*	*-1.16*	*-0.63*		*2.79*	*1.34*		*9.10**	*-1.93*		*1.30*	*0.28*
Put net-trade volume	-0.060	0.022	0.072	0.488	-1.518	0.065		0.005	0.001		-0.018	0.007		0.097	-0.001
	-1.27	*1.08*	*0.33*	*1.10*	*-6.05**	*2.38*		*1.73*	*-0.19*		*-0.92*	*1.57*		*11.12**	*-0.38*