Investigating the interaction between returns and order flow imbalances: Endogeneity, intraday variations, and macroeconomic news announcements*

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Abstract

The study examines the interaction between returns and order flow imbalances, constructed from the best bid and ask files of the S&P 500 E-mini futures contract, using a structural vector autoregressive (SVAR) model. The estimation results show that significant endogeneity exists and that the estimated parameters and associated quantities, such as the return variance driven by order flow imbalances, vary over time, reflecting intense or mild order submission activities. Further, order flow imbalances are shown to be more informative several minutes away from macroeconomic news announcements and that inactive order submission periods exist when they occur.

Keywords: High frequency data; Identification through heteroskedasticity; Intraday variation; Macroeconomic news announcement; Order flow imbalance; Structural vector autoregressive model.

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1 Introduction

Modern electronic trading is implemented with a limit order book (LOB), which is a collection of quotes at various price levels.[1] The LOB is updated by the arrival of new orders, which include limit orders, marketable orders, and cancellations of existing limit orders. The price change induced by such orders is called the price impact, and this reflects certain aspects of market liquidity. Such a price change can also induce marketable and limit orders or cancellations when traders adopt price-contingent trading strategies. Thus, the interaction between the price and orders is essential for understanding the price formation mechanism in modern electronic markets. Based on the foregoing, this study uses the best bid and offer (BBO) files of the S&P E-mini 500 futures contract to examine the price–orders interaction and ascertain its implications on associated quantities such as the return variance.

Investigating the source of price changes in financial markets has been a major issue in the market microstructure literature. For example, Hasbrouck (1991) shows that the price change depends on the size and sign of trades and the bid-ask spread (a proxy for liquidity) as well as current and past prices. The theoretical literature attributes these phenomena to information asymmetry.[2] The effect of trading and information flows on the price change has been investigated by, for example, Jones et al. (1994a,b) and Easley et al. (1997a,b).

Dufour and Engle (2000) extend Hasbrouck's vector autoregressive (VAR) model for prices and trade and show that as the time between trades decreases, the price impact of trades, the speed of price adjustment to trade-related information, and the positive autocorrelation of signed trades all increase. Further, Chung et al. (2005) show that the price impact is positively correlated to the notion of the probability of information-based trading, introduced and developed by Easley and O'Hara (1992) and Easley et al. (1997b). Various other aspects of the price impact have been studied in this large research body such as Bouchaud et al. (2002), Bouchaud et al. (2004), Bouchaud et al. (2006), Bouchaud et al. (2009) and the references therein.

At the highest frequency, the price impact of a single order is trivially measured as a mechanical price change, which depends on the depth of the LOB, especially outstanding limit orders on the best bid and ask quotes. Hautsch and Huang (2012) investigate the market impact of a single order by employing a cointegrated VAR model for quotes and depth. Such mechanical price changes are also illustrated in the stylized LOB model introduced by Cont et al. (2014). If the data are based on the arrival time of each order, one can simply measure the price impact by avoiding time aggregation, which may cause mutual dependence in orders.

However, the advanced technology and algorithmic trading systems that characterize modern markets allow traders to submit hundreds of orders every second.[3] At such ultra high

[1] Most financial markets, including leading exchanges such as the NASDAQ, the NYSE, and Euronext, employ electronic LOB systems.

[2] Bagehot (1971) was the first study to consider a model with heterogeneously informed traders (the so-called asymmetric information model) and this approach has since been analyzed and developed by studies such as Copeland and Galai (1983), Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990). This growing research stream is reviewed by, for example, O'Hara (1995) and Hasbrouck (2007).

[3] The round-trip communication time between New York and Chicago has recently been reduced to 8.1 milliseconds. See Budish et al. (2015) and the references therein for the details and problems induced by this

frequencies, it is costly to track the mechanical price change induced by each order. In addition, as shown by Boehmer et al. (2005), many limit orders are quickly canceled after their placement, which induces frequent changes in the LOB and makes the mechanical price impact of a single order untrustworthy. Thus, it is more realistic and sensible to measure or estimate the price impact of aggregated orders over a short interval such as a few seconds or minutes.

Cont et al. (2014) estimate the price impact of order flow imbalances (i.e., the differences between buy and sell orders) over 10-second intervals. For each 30-minute interval, they regress price changes on order flow imbalances. Their estimates of the price impact (OLS estimates of the coefficient of order flow imbalances) are found to be in line with their stylized LOB model. Moreover, the price impact estimates show a notable intraday pattern, which is high around the time the market opens but small around its close. This pattern differs from the U- or J-shaped patterns of market activities such as return volatility and trading volume, which have been widely observed in the literature.[4]

However, the ability to estimate the price impact of aggregated orders over a short interval by using simple regression analysis is debated. Price-contingent strategies imply that a price change may induce further order submissions in a subsequent period.[5] Thus, endogeneity exists in order flows during a short interval. By taking account of this endogeneity, Deuskar and Johnson (2011) jointly model returns and net order flows (buy orders minus sell orders) and estimate the price impact by using the identification through the heteroskedasticity (ITH) approach proposed by Rigobon (2003), Rigobon and Sack (2003, 2004), and Sentana and Fiorentini (2001).[6] Deuskar and Johnson (2011) confirm the existence of significant endogeneity in the flows and show that the price impact is time-varying and closely related to an illiquidity measure. In addition, Eisler et al. (2012) and Hautsch and Huang (2012) show complicated serial and cross-correlation structures of price changes and orders.

By taking into account the endogenous and dynamic interaction between price changes and orders, this study applies a structural VAR (SVAR) model to mid-quote returns and order flow imbalances constructed from the BBO files of the S&P 500 E-mini futures contract with time stamped at one second. The intraday variations are also considered by estimating

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high-frequency trading arms race.

[4]A number of studies show that market activities exhibit a U-shaped pattern over the trading day. Such activities are relatively high at the beginning of the trading day, decline at a decreasing rate, reach intraday lows around the middle of the day, and then increase at an increasing rate until the close. The shape can be asymmetric in that the value at the opening of the market is lower or higher than that at the close. Such an asymmetric pattern is sometimes referred to as a J- or reverse J-shaped pattern. For example, Wood et al. (1985) analyze NYSE-listed stocks and report a U-shaped pattern for minute-by-minute average returns and a reverse J-shaped pattern for the variability of returns. McInish and Wood (1992) report a crude J-shaped pattern for minute-by-minute spreads and Lee et al. (1993) report a U-shaped pattern for half-hour volumes and spreads. Additionally, Andersen and Bollerslev (1997) report a U-shaped pattern for five-minute absolute returns for S&P 500 stock index futures, although this drops and rises sharply before the close.

[5]See, for example, Obizhaeva (2008) and Obizhaeva and Wang (2013) for the optimal trading strategy in an LOB market.

[6]The ITH approach is often used for identifying shocks in VAR analysis. In particular, it has been used to identify monetary policy shocks by Rigobon and Sack (2003, 2004) and Lanne and Lütkepohl (2008). These studies use exogenous changes in the variances of the residuals. See Lütkepohl and Netšunajev (2017) for a review of models employing different heteroskedasticity structures.

the SVAR model for each 15-minute interval over the course of a day (8:30–15:00 Chicago Time). In particular, the contemporaneous parameters, that is, the coefficients of returns on the concurrent order flow imbalances and vice versa, as well as the standard deviations of orthogonal innovations are estimated by applying the ITH method to the residuals of the reduced-form VAR model. Therefore, this approach allows us to examine the interaction between returns and flows in light of both the intraday variations and the endogeneity.

An extensive empirical analysis shows that the proposed approach is useful to capture the complicated serial and cross-correlation structures of returns and order flows and confirms several of the findings offered by previous studies. Notably, the analysis shows the significant price impact (from order flow imbalances to returns) and flow impact (from returns to order flow imbalances) at one-second intervals. This finding, which is consistent with the results of Deuskar and Johnson (2011), confirms the endogeneity and upward bias in the OLS estimates.

Several notable results are also presented. Firstly, the price impact, estimated by using the ITH method in light of the endogeneity present, is consistent with that implied by the stylized LOB model of Cont et al. (2014). Secondly, the impulse responses indicate that most of the impacts of shocks in return and flow innovations disappear within one second and that the instantaneous and long-run impacts exhibit roughly the same intraday patterns. Thirdly, the estimated parameters and associated quantities exhibit significant intraday variations, which are related to variations in the variables such as the depth, number of order book events (buy and sell trades, limit orders on bid and ask, and cancellations), and average spread, reflecting some aspects of order submission activities.

As a source of public information affecting these order submission activities, the effect of macroeconomic news announcements is also examined. Previous studies such as Andersen and Bollerslev (1998), Andersen et al. (2003, 2007), and Hautsch et al. (2011) show that macroeconomic news announcements cause intense trading activity and a surge in return volatility. Consistent with the findings of these studies, the empirical analysis presented herein shows that macroeconomic news announcements affect the interaction between returns and flows as well as their variances. Specifically, these announcements increase the price impact and the variance driven by return innovations, whereas they decrease the flow impact and flow-driven variance. Additionally, order flow imbalances are more informative five to 10 minutes away from the announcement times but less informative around them, suggesting inactive order submission periods five minutes before and after such announcements.

The rest of this paper is organized as follows. Section 2 introduces the dataset of the S&P 500 E-mini futures contract as well as the construct variables, provides their summary statistics, and illustrates their intraday variations. Section 3 describes the model and estimation methodology. Section 4 presents the estimation results and impulse response analysis. Section 5 illustrates the intraday variations in the estimated parameters and associated quantities, which are linked to the variables reflecting some aspects of order submission activities. Section 6 investigates the effects of macroeconomic news announcements. Finally, Section 7 concludes the paper with discussions on further studies.

2 Data

The dataset used in this study is constructed from the BBO files of the S&P 500 E-mini futures contract obtained from CME Group.[7] The BBO file contains all events that change the price or size of the best bid and ask quotes. Specifically, it includes all transactions induced by marketable orders as well as all quote revisions induced by limit orders and cancellations. The data entries are date, contract month, time in seconds, trade sequence number, event classification number (0, 1, and 2 for ask, bid, and trade, respectively), price, and quantity. Multiple events within one second are recorded in the order of arrivals with a unique trade sequence number for the day.

The sample examined herein contains 1,490 trading days from January 2, 2008 to December 31, 2013.[8] For each day, observations taken from 8:30–15:00 Chicago Time are extracted, corresponding to the regular trading hours of the NYSE, where most of the S&P 500 components are traded. To ensure that the sample contains sufficient observations each day, the most active contract (highest daily trading volume) is selected.[9]

2.1 Variable Construction

From the BBO data, mid-quote returns, denoted by r_t, are computed every second. Order flow imbalances are constructed as suggested by Cont et al. (2014). Let P_n^a and q_n^a be the nth observations of the best ask price and its size (depth). Similarly, let P_n^b and q_n^b be the nth observations of the best bid price and its size. Then, an order book event is defined as

$$e_n = q_n^b I_{\{P_n^b \geq P_{n-1}^b\}} - q_{n-1}^b I_{\{P_n^b \leq P_{n-1}^b\}} - q_n^a I_{\{P_n^a \leq P_{n-1}^a\}} + q_{n-1}^a I_{\{P_n^a \geq P_{n-1}^a\}}, \tag{1}$$

where $I_{\{A\}}$ denotes the indicator function of event A. Order flow imbalances, denoted by f_t, are computed by aggregating e_n over one-second intervals.[10] Note that e_n represents a change in the order book at the best bid and ask induced by a marketable order, limit order, or cancellation. Hence, order flow imbalance f_t represents the imbalance between supply and demand at the best bid and ask prices.

[7] The E-mini is a liquid asset and most of the price discovery for the S&P 500 occurs in the E-mini market (e.g., Hasbrouck (2003)). The minimum contract size is \$50 times the futures price and the minimum tick size is 0.25 index points, which is equivalent to \$12.5 (= 50×0.25). It is traded for almost 24 hours from Mondays to Fridays. Regular trading starts at 8:30 Chicago Time (daylight savings time) and ends at 15:15. After a 15-minute break, electronic trading is available from 15:30 to 8:30 except for a 30-minute daily maintenance shutdown from 16:30. Contract months are March, June, September, and December and are available with the latest five months in the March quarterly cycle. Trading can occur up to 8:30 on the third Friday of the contract month.

[8] Several days with insufficient observations are removed from the sample. They are mostly before and after holidays and near the end of the year.

[9] The most active contract typically switches from the front month (nearest) contract to the next about a week before the last trading day of the nearest one.

[10] If order types are available, that is, if orders are categorized into market orders, limit orders, and cancellations on each side of the bid and ask, then order flow imbalance f_t can be computed as

$$f_t = L_t^b - C_t^b - M_t^b - L_t^a + C_t^a + M_t^a,$$

where M_t^b, M_t^a, L_t^b, L_t^a, C_t^b, and C_t^a are marketable orders, limit orders, and cancellations, on the best bid and ask prices, aggregated over the tth interval, respectively.

In addition, variables reflecting market activities are computed. The number of order book events and average size of events reflect how active and aggressive order submissions are, respectively. The average spread represents the transaction cost and the depth reflects certain aspects of market liquidity. The depth is estimated by averaging the sizes on the best bid and ask prices before or after a price change, that is,

$$D_t = \frac{1}{2}\left[\frac{\sum_{n\in I_t}\left(q_n^b I_{\{P_n^b < P_{n-1}^b\}} + q_{n-1}^b I_{\{P_n^b > P_{n-1}^b\}}\right)}{\sum_{n\in I_t} I_{\{P_n^b \neq P_{n-1}^b\}}} + \frac{\sum_{n\in I_i}\left(q_n^a I_{\{P_n^a > P_{n-1}^a\}} + q_{n-1}^a I_{\{P_n^a < P_{n-1}^a\}}\right)}{\sum_{n\in I_t} I_{\{P_n^a \neq P_{n-1}^a\}}}\right], \quad (2)$$

where I_t represents a one-second interval over which the variables are computed. The estimated depth, D_t, is consistent with the definition of depth in the stylized LOB model presented by Cont et al. (2014).

2.2 Summary Statistics

Table 1 presents the summary statistics of the mid-quote returns and order flow imbalances. They are roughly symmetric around zero and exhibit large variations compared with their means. The percentiles of order flow imbalances indicate that some intervals have intense order submissions on a single side of the bid or ask.

Table 1 also reports the summary statistics of the market activity variables. On average, 45 events occur and each event contains 15 contracts. For more than 5% of all one-second intervals (more than 1,725,000 intervals), hundreds of orders with over 50 contracts are submitted or canceled. Contrary to the large variations in these variables, the average spread is mostly equal to the minimum tick size of 0.25. Further, the depth is large compared with the average size of events.

Overall, therefore, the S&P 500 E-mini futures contract market is liquid and active. Consequently, multiple events exist within one second, which may cause endogeneity in the aggregated returns and flows. Thus, investigating the interaction between returns and flows without considering this endogeneity may bias the price impact estimate, as illustrated in Section 3.

2.3 Intraday Variations

Figure 1 shows the intraday variations in the standard deviations of returns and order flow imbalances as well as the means of the market activity variables. The standard deviations of the two series and means of the number and average size of events exhibit roughly U-shaped patterns, implying active and aggressive order submissions around the open and close of the market. Such a phenomenon has been commonly observed in a number of previous studies (see footnote 4).

Notably, in the last five-minute interval, 14:55–15:00, the standard deviation of order flow imbalances, mean of the average size of events, and mean of the depth increase significantly, whereas the standard deviation of returns and mean of the average spread drop. This finding implies that although there are more frequent and larger orders on the single side of the bid and ask, the return is less volatile because the market is liquid around the close. In addition, around 9:00, the standard deviation of returns and mean of the average spread jump, whereas the other four series drop. This finding implies that the market is illiquid in this short interval and thus that market participants refrain from submitting orders. This period is shown to be linked to macroeconomic news announcements in Section 6.

The observed intraday variations should also be considered when investigating the interaction between returns and flows. Section 3 introduces a model and estimation method that take account of the endogeneity as well as the serial and cross-correlations of returns and order flow imbalances. These intraday variations can also be considered by estimating the model for certain intervals during a day. Section 4 presents the estimation results for each 15-minute interval for each day.

3 Model and Estimation Methodology

This section describes the model and estimation methodology used in this study to investigate the interaction between asset returns and order flow imbalances. The model is based on the simultaneous equation of returns and order flows employed by Deuskar and Johnson (2011). Firstly, a simple bivariate model is introduced and the endogeneity problem is illustrated. Secondly, under a simple setup, an estimation technique that adopts the ITH method is described. Thirdly, an SVAR model, which takes into account the endogeneity and dynamic interaction between returns and order flow imbalances, is presented and the instantaneous and long-run impacts are defined. Lastly, given that the SVAR model is now fully identified, the flow-driven risk (FDR), namely the proportion of risk due to a shock in order flow imbalances, is introduced. In the following, order flow imbalances are frequently replaced by flows or order flows for simplicity.

3.1 Simple Bivariate Model

The impact from order flows to concurrent returns is captured by the following equation:

$$r_t = b_r f_t + \epsilon_{r,t}, \quad \epsilon_{r,t} \sim (0, \omega_r^2), \tag{3}$$

where r_t and f_t represent returns and order flows, respectively and $\epsilon_{r,t}$ is a return innovation with mean zero and variance ω_r^2. The coefficient b_r is the price impact, which reflects the effect of order flows on returns. In other words, the price impact coefficient b_r represents market illiquidity; here, a large value of b_r implies that the market is illiquid. Thus, the price impact b_r is zero when the market is perfectly liquid.

At the highest frequency, the price impact of a single order is a mechanical price change depending on the shape of the LOB. Specifically, under the stylized LOB model introduced by Cont et al. (2014), the price impact is approximately $1/2D$, where D represents the market depth or size of outstanding limit orders. By using NYSE Trades and Quotes data, Cont et al. (2014) construct the order flow imbalance as in Section 2 and verify that the price impact of order flow imbalances is close to that implied by the stylized LOB model.

The returns and flows are, however, usually computed over an interval containing multiple orders. Thus, they inevitably suffer from endogeneity (i.e., returns may induce further orders within the interval). Deuskar and Johnson (2011) attribute the source of causation to the presence of stale limit orders and price-contingent trading strategies, as discussed by Obizhaeva (2008) and Obizhaeva and Wang (2013). Taking account of the endogeneity present, Deuskar and Johnson (2011) therefore augment the return equation (3) by using the following flow equation:

$$f_t = b_f r_t + \epsilon_{f,t}, \quad \epsilon_{f,t} \sim (0, \omega_f^2), \tag{4}$$

where $\epsilon_{f,t}$ is a flow innovation with mean zero and variance ω_f^2 that is assumed to be uncorrelated with $\epsilon_{r,s}$ for any s. The coefficient b_f measures the impact from returns to concurrent order flows and is referred to as the flow impact hereafter. The flow impact b_f represents the intensity of price-contingent trading or endogeneity and should be zero in the absence of endogeneity.

The return and flow equations are summarized as the following simple bivariate model:

$$By_t = \epsilon_t, \quad \epsilon_t \sim (0, \Omega), \tag{5}$$

where $y_t = (r_t, f_t)'$, $\epsilon_t = (\epsilon_{r,t}, \epsilon_{f,t})'$, and matrices B and Ω are defined as

$$B = \begin{pmatrix} 1 & -b_r \\ -b_f & 1 \end{pmatrix}, \quad \Omega = \begin{pmatrix} \omega_r^2 & 0 \\ 0 & \omega_f^2 \end{pmatrix}. \tag{6}$$

This bivariate model can be rewritten as

$$r_t = \frac{1}{1 - b_r b_f}\epsilon_{r,t} + \frac{b_r}{1 - b_r b_f}\epsilon_{f,t}, \quad \epsilon_{r,t} \sim N(0, \omega_r^2), \tag{7}$$

$$f_t = \frac{b_f}{1 - b_r b_f}\epsilon_{r,t} + \frac{1}{1 - b_r b_f}\epsilon_{f,t}, \quad \epsilon_{f,t} \sim N(0, \omega_f^2). \tag{8}$$

Clearly, f_t and $\epsilon_{r,t}$ are correlated and a simple regression for the return equation (3) results in an inconsistent estimator of b_r:

$$\hat{b}_r - b_r \longrightarrow \frac{\mathrm{Cov}(f_t, \epsilon_{r,t})}{\mathrm{Var}(f_t)} = \frac{(1 - b_r b_f) b_f \omega_r^2}{b_f^2 \omega_r^2 + \omega_f^2} = \delta_{br}, \tag{9}$$

where $\hat{b}_r$ is the OLS estimator of b_r and δ_{br} represents the asymptotic bias of $\hat{b}_r$. Thus, when endogeneity exists, that is, $b_f \neq 0$, b_r cannot be consistently estimated by using OLS. Alternatively, one can estimate the parameters by using the ITH method described in the following subsection.

3.2 ITH Method

Let Σ be a variance-covariance matrix of y_t, that is,

$$\Sigma = \mathrm{Var}(y_t) = \begin{pmatrix} \sigma_r^2 & \sigma_{rf} \\ \sigma_{rf} & \sigma_f^2 \end{pmatrix}. \tag{10}$$

Then, taking the variance on both sides of (5) gives $B\Sigma B' = \Omega$, which reduces to the following three equations:

$$\sigma_r^2 - 2b_r\sigma_{rf} + b_r^2\sigma_f^2 - \omega_r^2 = 0, \tag{11}$$
$$\sigma_f^2 - 2b_f\sigma_{rf} + b_f^2\sigma_r^2 - \omega_f^2 = 0, \tag{12}$$
$$b_f\sigma_r^2 - (1 + b_r b_f)\sigma_{rf} + b_r\sigma_f^2 = 0. \tag{13}$$

The variances σ_r^2 and σ_f^2 as well as the covariance σ_{rf} can be estimated as the sample variances and covariance of y_t. Hence, there are four unknown parameters $(b_r, b_f, \omega_r, \omega_f)$ in the three equations, which implies that the parameters cannot be identified without additional restrictions.

To resolve this identification problem, the ITH method uses the heteroskedasticity of the variance-covariance matrix Σ given by (10). Suppose that there are S states across which the variances σ_r^2 and σ_f^2 as well as the covariance σ_{rf} change, whereas the price impact b_r and flow impact b_f in the matrix B remain the same. For each state $s = 1, 2, \dots, S$, there are three variance-covariance equations (11)–(13), where b_r and b_f remain the same over the states, while $\omega_{r,s}$ and $\omega_{f,s}$ vary over s.

In this case, there are $2 + 2S$ parameters in $3S$ equations. Provided that the equations are linearly independent over the states, the parameters are identified if $S \geq 2$.[11] Specifically, when $S \geq 2$, the parameters can be estimated by the generalized method of moments with $3S$ moment conditions constructed from the variance-covariance equations (11)–(13) for S states.

Deuskar and Johnson (2011) estimate the bivariate model by assuming that b_r and b_f are constant over the sample period, whereas the variances ω_r^2 and ω_f^2 vary over a day or over several days. They show that both b_r and b_f are significantly positive, that is, there is significant endogeneity in the flows, which causes simultaneity bias in the price impact.[12]

3.3 SVAR Model

The simple bivariate model (5) takes account of the endogeneity in flows but ignores the serial and cross-correlation structures in returns and flows. By taking into account both the endogeneity and the dynamic interaction between returns and order flows, the SVAR model is given by

$$By_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \epsilon_t, \quad \epsilon_t \sim (0, \Omega), \tag{14}$$

where matrices B and Ω are given in (6) and Φ_j's are 2×2 matrices governing the autocorrelations. The SVAR model can be written as the following reduced-form VAR model:

$$y_t = \tilde{c} + \tilde{\Phi}_1 y_{t-1} + \tilde{\Phi}_2 y_{t-2} + \cdots + \tilde{\Phi}_p y_{t-p} + \eta_t, \tag{15}$$

[11] See Rigobon (2003) for the estimation procedure and identification conditions in more general settings.

[12] Deuskar and Johnson (2011) call the estimated price impact b_r an unconditional price impact. To investigate a conditional (time-varying) price impact, they construct a slope measure by fitting a line through the depths on several levels (deeper than BBO), which is called the inverse slope of the limit order book (ILOBS). The ILOBS is designed to capture the expected effect of trade and hence is a measure of the price impact of potential trades. By using the ILOBS, they compute the time-varying price impact as $b_{r,t} = b_0 + b_1 ILOBS_t$.

where $\tilde{c} = B^{-1}c$, $\tilde{\Phi}_j = B^{-1}\Phi_j$ $(j = 1, 2, \dots, p)$, $\tilde{\psi} = B^{-1}\psi$ and $\eta_t = B^{-1}\epsilon_t$.

Taking the variance on both sides of $B\eta_t = \epsilon_t$ reduces to the variance-covariance equations (11)–(13) again. Therefore, the SVAR model can be estimated in two steps. First, the reduced-form VAR model (15) is estimated. Then, given the residuals $\hat{\eta}_t$, the price and flow impacts, b_r and b_f, as well as the standard deviations, ω_r and ω_f, are estimated by adopting the ITH method.

Once the SVAR model is fully identified, the impulse response functions to the innovations in returns and flows are computed in the usual manner. Let $IRF_{ij}(k)$ be the responses of i to a one-unit shock in the orthogonal innovations of j at lag k, where $i, j \in \{1, 2\} = \{r, f\}$. For instance, $IRF_{12}(k)$ or $IRF_{rf}(k)$ is the flow-to-return impact at lag k. Then, the cumulative impulse responses are computed as

$$I_{ij}(K) = \sum_{k=0}^{K} IRF_{ij}(k). \tag{16}$$

In the following, the response at lag $k = 0$, $I_{ij}(0) = IRF_{ij}(0)$, is referred to as the instantaneous impact. In addition, the long-run impact is defined as

$$I_{ij}(\infty) = \sum_{k=0}^{\infty} IRF_{ij}(k) = \left[(I_2 - \tilde{\Phi}_1 - \tilde{\Phi}_2 - \cdots - \tilde{\Phi}_p)^{-1} B^{-1}\right]_{ij}, \tag{17}$$

where I_2 is a 2×2 identity matrix and $[A]_{ij}$ denotes the (i, j) element of a matrix A.

3.4 FDR

Once the parameters are identified, the residuals in the returns of the reduced-form VAR model, $\eta_{r,t}$, can be expressed as

$$\eta_{r,t} = \frac{1}{1 - b_r b_f}\epsilon_{r,t} + \frac{b_r}{1 - b_r b_f}\epsilon_{f,t}, \tag{18}$$

where $1/(1 - b_r b_f)$ and $b_r/(1 - b_r b_f)$ indicate the effects of a one-unit shock of the orthogonal innovations ϵ_r and ϵ_f, corresponding to the instantaneous impacts $I_{rr}(0)$ and $I_{rf}(0)$, respectively. Then, the return variance conditional on past returns and order flow imbalances is computed as

$$\tau^2 = \mathrm{Var}[\eta_{r,t}] = \tau_r^2 + \tau_f^2, \quad \tau_r^2 = \frac{\omega_r^2}{(1 - b_r b_f)^2}, \quad \tau_f^2 = \frac{b_r^2 \omega_f^2}{(1 - b_r b_f)^2}, \tag{19}$$

where τ_r^2 and τ_f^2 are the conditional variances driven by the innovations in returns and in order flow imbalances, ϵ_r and ϵ_f, respectively.

Deuskar and Johnson (2011) define the FDR as the ratio of the conditional variance driven by a flow shock to total variance, that is,

$$FDR = \frac{\tau_f^2}{\tau_r^2 + \tau_f^2} = \frac{b_r^2 \omega_f^2}{\omega_r^2 + b_r^2 \omega_f^2}. \tag{20}$$

The FDR represents the proportion of risk due to the price impact b_r^2 inflated or deflated by ω_f^2. With ω_r^2 fixed, the FDR is larger when the order flow imbalance is more likely to drive price changes or it is more volatile, or possibly both. Therefore, the FDR reflects how informative the order flow imbalance is.

4 Estimation Results

This section presents the estimation results of the SVAR model (14) and associated analyses. Firstly, the estimation results of the reduced-form VAR model (15) are summarized. Secondly, the ITH estimation results of the contemporaneous parameters and associated quantities such as the conditional variances and FDR are presented. Thirdly, the dynamic interaction between returns and flows are analyzed by using impulse response analysis.

4.1 Reduced-form VAR Model

Table 2 presents the estimation results of the reduced-form VAR model (15) with the returns r_t and order flow imbalances f_t over one-second intervals. The model is estimated for each 15-minute interval for each day, resulting in 38,740 estimations. The number of lags p selected by using the Akaike information criterion is positive for 38,725 intervals out of these 38,740.

For the return equation, the coefficient of the first-order lag return r_{t-1}, denoted by $\tilde{\phi}_{1,rr}$, is significantly negative (the t-values are smaller than -2) for 94% of the intervals, indicating a return reversal at a one-second frequency interval. By contrast, the coefficient of the first-order lag order flow imbalance f_{t-1}, denoted by $\tilde{\phi}_{1,rf}$, is significantly positive (the t-values are greater than 2) for 83% of the intervals, which shows that the effect of an order flow imbalance on returns may last for several intervals.

For the flow equation, the coefficient of r_{t-1}, denoted by $\tilde{\phi}_{1,fr}$, is significantly positive for 22% of the intervals, whereas it is significantly negative for 15%. This finding indicates that returns affect subsequent flows at a significant rate. In addition, the coefficient of f_{t-1}, denoted by $\tilde{\phi}_{1,ff}$, is significantly positive for 43% and negative for 18%, implying that the effect of a return on the order flow imbalance may last for several seconds. In other words, endogeneity exists when returns and flows are aggregated over several seconds.

On average, the lagged returns and flows explain 8.7% and 4.6% of the variations in returns and flows, respectively. The R-squared values rise over 20% in some cases. These estimation results confirm the significant auto- and cross-correlation structures of the returns and order flow imbalances. Such correlation structures can be explored in more detail by impulse response analysis once the structural parameters have been estimated by using the ITH method.

4.2 Structural Parameters and Associated Quantities

For each 15-minute interval for each day, the structural parameters in (6) are estimated by applying the ITH method to the residuals $\hat{\eta}_t$. The price and flow impacts, b_r and b_f, are assumed to be positive and fixed in each 15-minute interval, whereas the standard deviations,

ω_r and ω_f, vary across the three five-minute subintervals. In other words, for each 15-minute interval, one set of (b_r, b_f) and three sets of (ω_r, ω_f) are estimated by using the ITH method.

Table 3 summarizes the estimation results. This table shows b_r varies substantially, ranging from almost zero (smaller than 0.0005) to nearly five and is statistically significant for 62% of the intervals. The mean is 0.815, which is roughly 70% higher than the conditional price impact of 0.474 implied by Deuskar and Johnson (2011), where returns and order flows are measured over one-minute intervals from 8:30 until 15:15.[13] This finding suggests that the price impact coefficient rises when returns and flows are measured over shorter intervals.[14]

By contrast, b_f varies moderately, ranging between zero and one for most intervals. It is also statistically significant for 70% of the intervals, confirming the endogeneity of order flow imbalances for these intervals even when they are measured over one second. The mean is 0.305, which is less than 60% of the estimate of 0.55 reported in Deuskar and Johnson (2011). This finding suggests that b_f decreases as the interval decreases, consistent with the suggestion that no endogeneity exists when returns and flows are measured for each event.

The standard deviations, ω_r and ω_f, are statistically significant for over 95% of the intervals and exhibit large variations. The summary statistics are similar across the three subintervals. However, there is sufficient heteroskedasticity in the return and flow variances to identify the parameters. In fact, the J-test statistic of Hansen (1982) indicates that the specified model is not rejected for 95% (nominal significant level) of the intervals.

Table 3 also reports the summary statistics of the OLS estimates, $\hat{b}_r$, differences between the OLS and ITH estimates, $\hat{b}_r - b_r$, and asymptotic bias, δ_{br} defined in (9). Clearly, $\hat{b}_r$ is significantly larger than the ITH estimate, that is, the OLS estimate is upward biased because of endogeneity. Further, $\hat{b}_r$ exhibits larger standard deviations. These findings are consistent with those presented by Deuskar and Johnson (2011), although those authors argue that simultaneity bias is not that large economically. The differences between the ITH and OLS estimates as well as asymptotic bias are further discussed in Section 5.

Given the parameter estimates of $(b_r, b_f, \omega_r, \omega_f)$, the conditional variance components, τ_r^2 and τ_f^2 defined in (19), and FDR, $FDR = \tau_f^2/(\tau_r^2 + \tau_f^2)$ defined in (20), are computed for each five-minute interval. Table 3 reports the summary statistics of the 116,220 estimates. Both τ_r^2 and τ_f^2 show substantial variations and the latter is almost zero for over 5% of the intervals (nearly 6,000 intervals), suggesting inactive order submission periods.

On average, FDR accounts for 17.5% of total risk (the return variance conditional on past returns and order flow imbalances). This is slightly greater than the FDR reported by Deuskar and Johnson (2011), 0.12–0.13, computed from the unconditional price impact. Although it is less than 0.3 for over 75% of the intervals, it varies substantially from almost zero to nearly 0.74, including the range of FDR reported in Deuskar and Johnson (2011), 0.41–0.72, computed from the conditional price impact. This finding indicates that the order

[13] Deuskar and Johnson (2011) estimate the conditional impact as $b_0 + b_1 ILOBS$, where $ILOBS$ is the illiquidity measure calculated over one-minute intervals. From their Tables 2 and 4, the mean of $ILOBS$ from February 2008 to January 2009 is 0.52, $b_0 = 0.11$, and $b_1 = 0.70$. Thus, the conditional price impact is approximately computed as $0.11 + 0.70 \times 0.52 = 0.474$.

[14] From February 2008 to January 2009, corresponding to the period considered in footnote 13, the ITH estimates of b_r are higher with a larger variation. The mean increases from 0.815 to 1.761 and the standard deviation from 0.988 to 1.669. Therefore, the different sample period is not the main source of the difference.

flow imbalance is informative for some intervals.

4.3 Impulse Responses

For each 15-minute interval for each day, the impulse responses induced by the shocks in return and flow innovations (return shocks and flow shocks hereafter) are computed. Figure 2 illustrates the medians of the 38,740 estimates of the impulse responses up to 10 lags as well as their 5th and 95th percentiles. All responses beyond lag 1 appear to be negligible, suggesting that the impacts of the shocks mostly disappear within a second. Such quick adjustments to these shocks are consistent with the results of Hautsch and Huang (2012), who show that quotes reach the new level after approximately 20 events, which is less than half of the average number of events in one second reported in Table 1.

Table 4 presents the summary statistics of the impulse responses at lags 0 and 1 and the long-run impacts defined in (17). The instantaneous impacts $IRF_{ij}(0)$ are mostly positive, which confirms the significant instantaneous impacts of a one-unit shock to return and flow innovations. The first-order lag impact from the return shock, $IRF_{rr}(1)$, is negative for more than 95% of the estimates because of the return reversal observed in the reduced-form VAR estimation results in Table 2. The rest of the first-order lag impacts appear to vary around zero and the signs are imprecisely determined.

The long-run impacts are all positive except for a proportion of $I_{fr}(\infty)$. On average, a one-unit flow shock, corresponding to an unexpected increase of 1,000 orders on either the bid or the ask side in a second, increases the return by 0.998 basis points in the same second ($IRF_{rf}(0)$) and by 1.392 basis points in the long run ($I_{rf}(\infty)$). From the ITH estimation results in Table 3, the mean standard deviation of flow innovations, ω_f, is 0.33, which is roughly half of the mean depth in Table 1. Thus, the long-run impact induced by flow shocks with half of the depth is roughly 0.46 ($\approx 0.33 \times 1.392$). This figure is comparable to 0.5–0.6 basis points, the permanent price impact of a limit order with half of the depth reported in Hautsch and Huang (2012).

5 Intraday Variations and Market Activity

This section presents the intraday variations in the estimated parameters and associated quantities and discusses some of the sources of these variations. Firstly, the intraday variations are presented and related to the market activity variables. Secondly, the sources of the variations are examined by using regressions with the estimated parameters and associated quantities as the dependent variables.

5.1 Intraday Variations

Parameters in the reduced-form VAR model: Figure 3 presents the averages of the first-order lag coefficients of the reduced-form VAR model (15) for each 15-minute interval from 8:30 until 15:00. For the equation of return r_t, the coefficient of the first-order lag return r_{t-1}, denoted by $\tilde{\phi}_{1,rr}$, starts with the lowest value in 8:30–8:45, jumps in 9:00–9:15, and subsequently drops. It then increases until 11:30 and mildly fluctuates slightly above the mean for the remainder of the day. This finding indicates that the return reversal is more prominent in the first 30 minutes of the trading day. On the contrary, the coefficient of the first-order lag flow f_{t-1}, denoted by $\tilde{\phi}_{1,rf}$, decreases until 10:15 and then increases, peaking at 13:30–13:45. It drops substantially in the last interval 14:45–15:00, indicating the smaller effect of f_{t-1} on r_t in that period.

For the flow equation f_t, the coefficient of r_{t-1}, denoted by $\tilde{\phi}_{1,fr}$, starts with a relatively low value, fluctuates around the mean until 14:45, and then drops substantially. Similar to $\tilde{\phi}_{1,rf}$, this shows that f_t is less sensitive to r_{t-1} in the last interval (14:45–15:00). By contrast, the coefficient of f_{t-1}, denoted by $\tilde{\phi}_{1,ff}$, exhibits a roughly J-shaped pattern with a significant increase in 14:45–15:00. This finding implies that order flow imbalances are highly autocorrelated and induce more subsequent flows in the last interval, which is consistent with the active and aggressive order submissions illustrated in Figure 1.

Structural parameters and bias: Figure 4 presents the averages of the price and flow impacts, b_r and b_f, for each 15-minute interval from 8:30 until 15:00. b_r exhibits a similar variation to $\tilde{\phi}_{1,rf}$, suggesting that contemporaneous and lagged order flows affect returns in a similar manner. It starts with a high value in 8:30–9:15, drops in 9:15–9:30, and gradually increases after 9:45. It then reaches the highest value in 13:00–13:15 and decreases with a significant drop to the lowest value in the last interval (14:45–15:00).

On the contrary, b_f increases in 8:45–9:15 and gradually decreases until 12:00. It reaches its lowest value in 12:45–13:00 and then surges to the highest value in the last interval. These results indicate that in the last interval (14:45–15:00), returns are less sensitive to order flow imbalances, whereas flows are much more dependent on returns. This fact is not surprising given that the market is liquid and active in that interval, as shown in Figure 1.

Figure 4 also presents the averages of the standard deviations of return and flow innovations, ω_r and ω_f, for each five-minute interval from 8:30 until 15:00. Roughly speaking, ω_r and ω_f reflect the intraday variations in the standard deviations of returns and order flow imbalances in Figure 1, respectively. Notably, ω_f increases significantly in the last five-minute interval (14:55–15:00). This result is in line with the sharp increase in the standard deviation of flows and the mean of the average size of events in Figure 1, reflecting active and aggressive order submissions in that interval. In addition, ω_r jumps in 9:00–9:05, while ω_f drops in 8:55–9:00, as observed in Figure 1, which is shown to be related to macroeconomic news announcements in Section 6.

Additionally, Figure 4 presents the averages of the difference between the OLS and ITH estimates, $\hat{b}_r - b_r$, and the asymptotic biases, δ_{br} defined in (9), for each 15-minute interval. Their intraday variations are almost identical. They start with low values, rise and fall in 9:15–10:15, peak in 13:30–13:45, and then decrease, dropping sharply in the last interval. Apart from the initial low values, the intraday variations appear to reflect that of b_r. Although both $\hat{b}_r - b_r$ and δ_{br} plummet to below 0.55 in 14:55–15:00, they are still large compared with b_r (i.e., around 0.55), indicating that significant endogeneity exists during the course of a day.

Instantaneous and long-run impacts: Figure 5 presents the medians of the instantaneous and long-run impacts, $I_{ij}(0)$ and $I_{ij}(\infty)$, for each 15-minute interval. Both flow-to-return impacts, $I_{rf}(0)$ and $I_{rf}(\infty)$, present almost the same pattern, which is similar to the intraday variation in the price impact b_r. On the contrary, the return-to-flow impacts, $I_{fr}(0)$ and $I_{fr}(\infty)$, show a pattern similar to the flow impact b_f. Therefore, properly estimating the price and flow impacts is important for investigating the instantaneous and long-run impacts.

Both return-to-return impacts, $I_{rr}(0)$ and $I_{rr}(\infty)$, exhibit similar intraday variations. They jump in 9:00–9:15 and increase in the last several intervals. The difference between the instantaneous and long-run impacts reflects the significant negative first-order lag impact, $IRF_{rr}(1)$, reported in Table 4. Similar intraday variations are observed in the flow-to-flow impacts, $I_{ff}(0)$ and $I_{ff}(\infty)$; however, the difference between the instantaneous and long-run impacts is large in 14:45–15:00. This finding implies that the impact of flow shocks lasts longer, especially in the last interval, reflecting the active and aggressive order submissions in the last five-minute interval, as illustrated in Figure 1.

Conditional variances and the FDR: Figure 6 presents the averages of the variance components driven by innovations in returns and order flow imbalances, τ_r^2 and τ_f^2, and the FDR, $FDR = \tau_f^2/(\tau_r^2 + \tau_f^2)$, for each five-minute interval from 8:30 until 15:00. τ_r^2 exhibits a variation similar to ω_r presented in Figure 4. By contrast, τ_f^2 presents a unique intraday variation. It is high in 8:30–9:30 with a large drop in 8:55–9:00 and roughly a U-shape in 9:30–14:45. It then declines sharply in 14:45–14:50 and leaps in 14:55–15:00.

For FDR, the plunge and surge in 14:45–15:00 are amplified by τ_r^2 and τ_f^2 moving in the opposite direction. Reflecting the increase in τ_r^2 and substantial decrease in τ_f^2, FDR drops to below 10% in 14:45–14:50, indicating that the order flow imbalance is uninformative in that interval. On the contrary, because of the decrease in τ_r^2 and substantial increase in τ_f^2, it rises to over 25% in 14:55–15:00, implying that the order flow imbalance is informative in the last interval.

5.2 Sources of Variations

Figures 3–6 illustrate the significant intraday variations in the estimated parameters and associated quantities. Some variations appear to reflect the market activity variables such as the depth and number of events. This subsection examines the sources of variations by regressing each of the estimated parameters and associated quantities on the market activity variables.

The dependent variables include the reciprocal of depth defined in (2), denoted by D^{-1}, number of events NE, average size of events ASE, and average spread SPR, computed over five- or 15-minute intervals according to the dependent variables. These variables reflect some aspects of the market and order submission activities. The market is illiquid when D^{-1} is large, order submissions are active when NE is large, they are aggressive when ASE is large, and the transaction cost is high when SPR is high. In addition, the time effect is controlled for by using dummies for the five- or 15-minute intervals and for the years.

Price and flow impacts, bias, and instantaneous impacts: Table 5 presents the regression results with the variables over 15-minute intervals. For b_r, the coefficient of D^{-1} is significantly positive, indicating that order flow imbalances have a more contemporaneous impact on returns when the market is illiquid. This finding is in line with Deuskar and Johnson (2011), showing that their illiquidity measure is a good proxy for the expected price impact. Additionally, the coefficient of D^{-1} for b_r is roughly 0.5, consistent with the price impact implied by the stylized LOB model of Cont et al. (2014). The coefficients of NE and ASE are both significantly negative, suggesting that flows have less impact on contemporaneous returns when order submissions are active and aggressive. Further, b_r decreases when the spread widens or the transaction cost is high. Along with the dummies for the 15-minute intervals and years, these variables explain about 54% of the variation in b_r.

A contrasting result is observed for b_f. The coefficients of D^{-1} and SPR are significantly negative and positive, respectively, implying that returns induce more flows when the market is illiquid and the transaction cost is high. Although the coefficient of NE is not significant, that of ASE is significantly positive. Thus, order flow imbalances are more sensitive to returns when order submissions are more aggressive. About 26% of the variation in b_f is explained by these variables and dummies. The explanatory power is almost half of that for b_r, implying that missing variables or market activities make flows more sensitive to returns.

The regression results for $\hat{b}_r - b_r$ and δ_{br} are almost identical as expected and are qualitatively the same as that for b_r. That is, bias increases when the market is illiquid. On the contrary, it decreases when there are more active and aggressive order submissions and the transaction cost is high. Thus, when a market is illiquid and inactive with a large spread, it is important to properly handle endogeneity bias.

It is not surprising that the instantaneous flow-to-return and return-to-flow impacts, $I_{rf}(0)$ and $I_{fr}(0)$, show similar results to b_r and b_f, respectively. On the contrary, the regression result for the instantaneous return-to-return impact, $I_{rr}(0)$, which is equivalent to the flow-to-flow impact $I_{ff}(0)$, is rather distinct. $I_{rr}(0)$ increases when there are active order submissions but decreases when there are aggressive order submissions and the transaction cost is high. Along with an R-squared value around 25%, this finding implies that missing factors make returns and flows more strongly affected by their own shocks.

Standard deviations, conditional variances, and the FDR: Table 6 presents the regression results with the variables over five-minute intervals. The results for standard deviations, ω_r and ω_f, are qualitatively the same. All coefficients are significantly positive, indicating that ω_r and ω_f increase when the market is illiquid, order submissions are active and aggressive, and the transaction cost is high. Along with the dummies, these variables explain roughly 45% and 47% of the variation in ω_r and ω_f, respectively. Similar results are observed for the variance components, τ_r^2 and τ_f^2; however, the coefficient of D^{-1} is not significant for τ_f^2 with a relatively low R-squared value.

On the contrary, the regression result for the FDR, FDR, is similar to those for b_r, although the coefficient of D^{-1} is not significant. The coefficients of NE, ASE, and SPR are significantly negative, indicating that FDR decreases when there are active and aggressive order submissions and the transaction cost is high. The adjusted R-squared value is low compared with the other dependent variables, indicating that FDR is hardly explained by the variables constructed from the order submissions on the best bid and ask prices.

6 Effects of Macroeconomic News Announcements

The previous section showed that the estimated parameters and associated quantities vary significantly over time. The variations are related to the market activity variables. These variables are the results of order submission activities that reflect both private and public information (e.g., O'Hara (1995) and Hasbrouck (2007)).

In terms of the latter information type, macroeconomic news announcements are an important source that affect trading outcomes. For instance, Andersen et al. (2003, 2007) and Hautsch et al. (2011) show that macroeconomic news announcements cause intense trading activity and a surge in return volatility. Further, Brogaard et al. (2014) show that high-frequency traders' trading is related to macroeconomic news announcements as well as the LOB.

Based on the foregoing, this section examines the effect of the eight announcements considered in Brogaard et al. (2014): construction spending, consumer confidence, existing home sales, factory orders, ISM manufacturing index, ISM service, leading indicators, and wholesale inventories. Most announcements are released at 9:00 Chicago Time.[15]

Figure 7 presents the averages of cumulative returns and order flow imbalances around positive and negative macroeconomic news announcements, which are considered to be negative if the announced value of the macroeconomic indicator is less than the consensus value and positive otherwise. Both returns and flows appear to move in the direction of the announcements. They start to decrease (increase) one second before the negative (positive) announcements are released, suggesting that the market reflects the incoming public information before it is released.

The announcement effects on the estimated parameters and associated quantities are examined by regression analysis with two announcement dummies, ANN_t and ANN_t^-. The first dummy takes one if the announcements are released in the tth five- or 15-minute interval and zero otherwise, whereas the second dummy takes one if the negative announcements are released in the tth interval and zero otherwise. Several lags are also included to take account of the pre- and post-announcement effects. The independent variables include the market activity variables, D^{-1}, NE, ASE, and SPR, as well as the interval and year dummies.

6.1 Price and Flow Impacts, Bias, and Instantaneous Impacts

Table 7 presents the regression results with the announcement dummies over 15-minute intervals. The coefficients of the other variables are almost identical to those in Table 5 and thus omitted for brevity. For b_r, the coefficient of ANN_t is not significant, whereas that of ANN_{t-1} is significantly positive, indicating that order flow imbalances induce larger price changes before such news announcements. Moreover, the coefficient of ANN_t^- is significantly positive, implying that order flows affect returns more strongly after negative news.

For b_f, the coefficients of ANN_t and ANN_{t-1} are both significantly negative, indicating that order flow imbalances are less sensitive to returns before and after announcements. The

[15]Those announcements not released at 9:00 Chicago Time are as follows: ISM service released at 7:55 on February 5, 2008 and at 10:00 on August 5, 2008; and consumer confidence at 8:37 on June 28, 2011.

coefficient of ANN_t^- is significantly negative, while that of ANN_{t-1}^- is not significant. That is, negative announcements further attenuate the flow impact when they occur.

The regression results for $\hat{b}_r - b_r$ show that the difference between the OLS and ITH estimates decreases both before and after macroeconomic news announcements. This finding is consistent with the result that b_f decreases around such announcements, attenuating endogeneity bias. On the contrary, negative announcements do not affect the difference. As expected, an almost identical result is obtained for the asymptotic bias δ_{br} defined in (9).

For the return-to-return impact $I_{rr}(0)$, which is equivalent to the flow-to-flow impact $I_{ff}(0)$, none of the announcement dummies are significant. By contrast, for the flow-to-return impact $I_{rf}(0)$, the regression results are qualitatively the same as those for b_r, indicating that the contemporaneous price impact b_r is the main driver of the instantaneous impact $I_{rf}(0)$. In the same manner, the regression results for the return-to-flow impact $I_{fr}(0)$ are in line with those for b_f. These results confirm that properly estimating price and flow impacts, b_r and b_f, is essential for investigating the interaction between returns and flows.

6.2 Standard Deviations, Conditional Variances, and FDR

Table 8 presents the regression results with the announcement dummies over five-minute intervals. Again, the coefficients of the other variables are almost identical to those in Table 5 and thus omitted for brevity. For ω_r, the coefficients of ANN_t and ANN_{t-1} are significantly positive, whereas those of ANN_{t+1} and ANN_{t-2} are significantly negative, indicating that ω_r gradually increases and decreases around macroeconomic news announcements. This finding is consistent with that of Hautsch et al. (2011) showing that news announcements have a highly positive impact on return volatilities followed by a gradual decline. Note that this announcement effect explains the large jump in ω_r in 9:00–9:05 shown in Figure 4. The coefficient of ANN_{t-1}^- indicates that negative announcements further increase ω_r before they occur, implying that negative news is anticipated and partly reflected in return volatility before its release.

For ω_f, the coefficients of ANN_t, ANN_{t-1}, ANN_{t-1}^-, and ANN_{t-2}^- are significantly negative. This finding indicates that order flow imbalances are less volatile around the announcements, suggesting that market participants refrain from submitting orders before new public information is released and absorbed into prices.

The announcement effect on the conditional variance driven by return innovations, τ_r^2, is qualitatively the same as that on ω_r. τ_r^2 decreases five to 10 minutes before the announcements, increases before and after five minutes around them, and then decreases. On the contrary, the conditional variance driven by flow innovations, τ_f^2, increases five to 10 minutes before and 10–15 minutes after the announcements but does not change for the 10 minutes around the release.

The coefficients of $FDR = \tau_f^2/(\tau_r^2+\tau_f^2)$ are qualitatively opposite to those of τ_r^2, suggesting that the flow-driven variance τ_f^2 is dominated by the non-flow-driven variance τ_r^2. FDR increases five to 10 minutes before the announcements, decreases during the five minutes around them, and then increases. In other words, order flow imbalances are more informative five to 10 minutes away from macroeconomic news announcements but are less informative around the time they occur. This result is in line with the inactive order submission period implied by the regression result for ω_f.

7 Conclusion

This study investigates the interaction between returns and order flow imbalances constructed from the BBO files of the S&P 500 E-mini futures contract, using the SVAR model in light of the intraday variations and endogeneity caused by time aggregation. Intraday variations are considered by applying the SVAR model to each 15-minute interval for each day and endogeneity is handled by estimating the structural parameters by using the ITH method.

The empirical analysis shows that the proposed approach is useful to capture the complicated serial and cross-correlation structures of returns and order flows and confirms several of the findings put forward by previous studies. Notably, the present study finds significant price and flow impacts (an impact from order flow imbalances to returns and vice versa) during one-second intervals. This finding is consistent with that of Deuskar and Johnson (2011), confirming the endogeneity and upward bias in the OLS estimates.

Several notable results are also presented. Firstly, the price impact, estimated by using the ITH method owing to the endogeneity present, as mentioned above, is consistent with that implied by the stylized LOB model of Cont et al. (2014). Secondly, the impulse responses indicate that most of the impacts of the shocks in return and flow innovations disappear within one second and that the instantaneous and long-run impacts exhibit roughly the same intraday patterns. Thirdly, the estimated parameters and associated quantities exhibit significant intraday variations, which are related to the variations in variables such as the depth, number of order book events (buy and sell trades, limit orders on bid and ask, and cancellations), and average spread, reflecting some aspects of the market and order submission activities.

Moreover, the effect of macroeconomic news announcements is examined. Such announcements increase the price impact as well as the variance driven by return innovations, whereas they decrease the flow impact and flow-driven variance. Overall, order flow imbalances are more informative five to 10 minutes away from these news announcements but are less informative around them, suggesting inactive order submission periods around the time they occur.

Extending the proposed framework to a multivariate setting is a natural direction of further study. Under the multivariate SVAR model, different order book events could be specified separately as in Eisler et al. (2012) and Hautsch and Huang (2012). Furthermore, the use of a multivariate model would allow us to investigate the interactions between price changes and orders in multiple markets. Budish et al. (2015) find that the S&P E-mini 500 futures contract and SPDR S&P 500 exchange-traded fund are nearly perfectly correlated over the course of the trading day as well as of an hour and a minute. Modeling the price changes and order flows of these two financial instruments may thus shed light on the price discovery process across both markets. Such issues remain objects of further study.

References

Admati, A. R. and Pfleiderer, P. (1988). A theory of intraday patterns: Volume and price variability. *Review of Financial Studies*, 1(1):3–40.

Andersen, T. G. and Bollerslev, T. (1997). Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance*, 4(2-3):115–158.

Andersen, T. G. and Bollerslev, T. (1998). Deutsche mark-dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. *Journal of Finance*, 53(1):219–265.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2003). Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. *American Economic Review*, 93(1):38–62.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2007). Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, 73(2):251–277.

Bagehot, W. (1971). The only game in town. *Financial Analysts Journal*, 27(2):12–14.

Boehmer, E., Saar, G., and Yu, L. (2005). Lifting the Veil: An Analysis of Pre-trade Transparency at the NYSE. *Journal of Finance*, 60(2):783–815.

Bouchaud, J.-P., Farmer, J. D., and Lillo, F. (2009). How markets slowly digest changes in supply and demand. In Hens, T. and Schenk-Hoppé, K. R., editors, *Handbook of Financial Markets: Dynamics and Evolution*, chapter 2, pages 57–160. Elsevier, 1st edition.

Bouchaud, J.-P., Gefen, Y., Potters, M., and Wyart, M. (2004). Fluctuations and response in financial markets: the suble nature of 'random' price changes. *Quantitative Finance*, 4(2):176–190.

Bouchaud, J.-P., Kockelkoren, J., and Potters, M. (2006). Random walks, liquidity molasses and critical response in financial markets. *Quantitative Finance*, 6(2):115–123.

Bouchaud, J.-P., Mézard, M., and Potters, M. (2002). Statistical properties of stock order books: empirical results and models. *Quantitative Finance*, 2(4):251–256.

Brogaard, J., Hendershott, T., and Riordan, R. (2014). High-frequency trading and price discovery. *Review of Financial Studies*, 27(8):2265–2306.

Budish, E., Cramton, P., and Shim, J. (2015). The high-frequency trading arms race: Frequent batch auctions as a market design response. *Quarterly Journal of Economics*, 130(4):1547–1621.

Chung, K. H., Li, M., and McInish, T. H. (2005). Information-based trading, price impact of trades, and trade autocorrelation. *Journal of Banking & Finance*, 29(7):1645–1669.

Cont, R., Kukanov, A., and Stoikov, S. (2014). The price impact of order book events. *Journal of Financial Econometrics*, 12(1):47–88.

Copeland, T. E. and Galai, D. (1983). Information effects on the bid-ask spread. *Journal of Finance*, 38(5):1457–1469.

Deuskar, P. and Johnson, T. C. (2011). Market Liquidity and Flow-driven Risk. *Review of Financial Studies*, 24(3):721–753.

Dufour, A. and Engle, R. F. (2000). Time and the price impact of a trade. *Journal of Finance*, 55(6):2467–2498.

Easley, D., Kiefer, N. M., and O'Hara, M. (1997a). The informaiton content of the trading process. *Journal of Empirical Finance*, 4(2-3):159–186.

Easley, D., Kiefer, N. M., and O'Hara, M. (1997b). One day in the life of a very common stock. *Review of Financial Studies*, 10:805–835.

Easley, D. and O'Hara, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics*, 19(1):69–90.

Easley, D. and O'Hara, M. (1992). Time and the Process of Security Price Adjustment. *Journal of Finance*, 47(2):577–605.

Eisler, Z., Bouchaud, J.-P., and Kockelkoren, J. (2012). The price impact of order book events: Market orders, limit orders and cancellations. *Quantitative Finance*, 12(9):1395–1419.

Foster, F. D. and Viswanathan, S. (1990). A theory of the interday variations in volume, variance, and trading costs in securities markets. *Review of Financial Studies*, 3(4):593–624.

Glosten, L. R. and Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1):71–100.

Hansen, L. P. (1982). Large sample properties of generalized method of mements estimators. *Econometrica*, 50(4):1029–1054.

Hasbrouck, J. (1991). Measuring the Information Content of Stock Trades. *Journal of Finance*, 46(1):179–207.

Hasbrouck, J. (2003). Intraday price formation in u.s. equity index markets. *Journal of Finance*, 58(6):2375–2399.

Hasbrouck, J. (2007). *Empirical Market Microstructure: The Institutions, Economics and Econometrics of Securities Trading*. Oxford University Press, New York.

Hautsch, N., Hess, D., and Veredas, D. (2011). The impact of macroeconomic news on quote adjustments, noise, and informational volatility. *Journal of Banking & Finance*, 35(10):2733–2746.

Hautsch, N. and Huang, R. (2012). The market impact of a limit order. *Journal of Economic Dynamics and Control*, 36(4):501–522.

Jones, C. M., Kaul, G., and Lipson, M. L. (1994a). Information, trading, and volatility. *Journal of Financial Economics*, 36(1):127–154.

Jones, C. M., Kaul, G., and Lipson, M. L. (1994b). Transactions, volume, and volatility. *Review of Financial Studies*, 7(4):631–651.

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica*, 53(6):1315–1335.

Lanne, M. and Lütkepohl, H. (2008). Indentifying monetary policy shocks via changes in volatility. *Journal of Money, Credit and Banking*, 40(6):1131–1149.

Lee, C. M. C., Mucklow, B., and Ready, M. J. (1993). Spreads, depths, and the impact of earnings information: An intraday analysis. *Review of Financial Studies*, 6(2):345–374.

Lütkepohl, H. and Netšunajev, A. (2017). Structural vector autoregressions with heteroskedasticity: A review of different volatility models. *Econometrics and Statistics*, 1:2–18.

McInish, T. H. and Wood, R. A. (1992). An Analysis of Intraday Patterns in Bid/Ask Spreads for NYSE Stocks. *The Journal of Finance*, 47(2):753.

Obizhaeva, A. (2008). Price Impact and Spread: Application of Bias-Free Estimation Methodology to Portfolio Transitions. Working Paper.

Obizhaeva, A. A. and Wang, J. (2013). Optimal trading strategy and supply/demand dynamics. *Journal of Financial Markets*, 16(1):1–32.

O'Hara, M. (1995). *Market Microstructure Theory*. Blackwell, Oxford.

Rigobon, R. (2003). Identification through heteroskedasticity. *Review of Economics and Statistics*, 85(4):777–792.

Rigobon, R. and Sack, B. (2003). Measuring the reaction of monetary policy to the stock market. *The Quarterly Journal of Economics*, 118:639–669.

Rigobon, R. and Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51:1553–1575.

Sentana, E. and Fiorentini, G. (2001). Identification, estimation and testing of conditionally heteroskedastic factor models. *Journal of Econometrics*, 102(2):143–164.

Wood, R. A., McInish, T. H., and Ord, J. K. (1985). An Investigation of Transactions Data for NYSE Stocks. *The Journal of Finance*, 40(3):723–739.

Table 1: Summary statistics of the mid-quote return, order flow imbalance, number of order book events, average size of order book events, average spread, and depth defined in (2). The statistics are computed from 34,512,298 samples of returns, flow, and the number and average size of events, and from 5,874,016 samples of the depth, computed for one-second intervals.

	Mean	SD	1%	5%	25%	50%	75%	95%	99%
Mid-Quote Return*	0.00	0.91	-2.86	-1.78	0.00	0.00	0.00	1.78	2.87
Order Flow Imbalance***	-0.00	0.52	-1.60	-0.48	-0.03	0.00	0.03	0.47	1.59
Number of Events**	0.45	0.66	0.01	0.03	0.10	0.23	0.51	1.72	3.27
Average Size of Events**	0.15	0.36	0.01	0.01	0.03	0.06	0.13	0.59	1.43
Average Spread	0.25	0.01	0.25	0.25	0.25	0.25	0.25	0.26	0.30
Depth***	0.63	0.43	0.07	0.12	0.33	0.55	0.84	1.43	2.05

* in basis points, ** in the hundreds, *** in the thousands

Table 2: Estimation results of the reduced-form VAR model (15). The model is estimated for each 15-minute interval for each day, resulting in 38,740 estimations. The number of lags p, selected by the Akaike information criterion, is positive for 38,725 intervals. $\tilde{\phi}_{1,rr}$, $\tilde{\phi}_{1,rf}$, $\tilde{\phi}_{1,fr}$, and $\tilde{\phi}_{1,ff}$ denote the (1,1), (1,2), (2,1), and (2,2) elements of $\tilde{\Phi}_1$, respectively. For the parameter estimates, t^+ represents the proportion of samples where the coefficient is significantly positive, i.e., the t-value of the coefficient is greater than 2, whereas t^- represents that where the coefficient is significantly negative. R_r^2 and R_f^2 denote the R-squared values for the return and flow equations, respectively. The summary statistics of the parameters and R-squared values are computed from the 38,725 samples excluding 15 samples with $p = 0$.

	Mean	SD	1%	5%	25%	50%	75%	95%	99%	t^+	t^-
p	5.568	4.703	1	2	3	4	7	14	26	—	—
$\tilde{\phi}_{1,rr}$	-0.312	0.132	-0.604	-0.520	-0.402	-0.314	-0.223	0.091	-0.000	0.00	0.94
$\tilde{\phi}_{1,rf}$	0.464	0.541	-0.187	0.018	0.183	0.319	0.548	1.437	2.766	0.83	0.01
$\tilde{\phi}_{1,fr}$	0.003	0.095	-0.241	-0.142	-0.045	-0.001	0.048	0.161	0.276	0.22	0.15
$\tilde{\phi}_{1,ff}$	0.041	0.177	-0.490	-0.318	-0.038	0.074	0.152	0.276	0.372	0.43	0.18
R_r^2	0.087	0.058	0.008	0.019	0.044	0.074	0.119	0.195	0.264	—	—
R_f^2	0.046	0.045	0.002	0.006	0.018	0.032	0.057	0.130	0.227	—	—

Table 3: Estimation results of the structural parameters in (6) and associated quantities. For each 15-minute interval for each day, the price and flow impacts (b_r, b_f) and three sets of standard deviations $(\omega_{r,1}, \omega_{r,2}, \omega_{r,3}, \omega_{f,1}, \omega_{f,2}, \omega_{f,3})$ are estimated by using the ITH method, resulting in 38,740 estimations. For the parameter estimates, the last column $*$ represents the proportion of intervals where the coefficient is statistically significant, that is, the t-value is greater than two in absolute value. J denotes the J-test statistic of Hansen (1982). For the J-statistic, the last column $*$ represents the proportion of intervals where the specified model is not rejected at 5%. $\hat{b}_r$ represents the OLS estimate of b_r and δ_{br} the asymptotic bias of $\hat{b}_r$ defined in (9). The summary statistics of the 116,220 estimates of the conditional variances, τ_r^2 and τ_f^2 defined in (19), and the FDR, $FDR = \tau_f^2/(\tau_r^2 + \tau_f^2)$ defined in (20), are also reported.

	Mean	SD	1%	5%	25%	50%	75%	95%	99%	$*$
b_r	0.815	0.988	0.000	0.000	0.230	0.542	1.043	2.519	4.871	0.62
b_f	0.305	0.245	0.000	0.000	0.134	0.249	0.426	0.779	1.097	0.70
$\omega_{r,1}$	0.561	0.405	0.105	0.185	0.325	0.463	0.700	1.264	2.113	0.97
$\omega_{r,2}$	0.541	0.380	0.099	0.177	0.315	0.452	0.648	1.208	2.025	0.97
$\omega_{r,3}$	0.540	0.390	0.101	0.178	0.313	0.448	0.643	1.210	2.046	0.97
$\omega_{f,1}$	0.339	0.240	0.062	0.100	0.184	0.275	0.418	0.806	1.210	0.96
$\omega_{f,2}$	0.334	0.232	0.061	0.099	0.181	0.273	0.413	0.779	1.217	0.96
$\omega_{f,3}$	0.339	0.244	0.060	0.098	0.181	0.273	0.419	0.806	1.239	0.96
J	1.092	1.414	0.000	0.006	0.142	0.569	1.505	3.961	6.432	0.95
$\hat{b}_r$	1.505	1.546	0.196	0.292	0.566	1.030	1.869	4.296	8.287	1.00
$\hat{b}_r - b_r$	0.690	0.933	-0.073	-0.013	0.173	0.409	0.857	2.286	4.647	—
δ_{br}	0.725	0.953	0.000	0.000	0.191	0.437	0.897	2.362	4.781	—
τ_r^2	0.621	1.702	0.013	0.041	0.130	0.273	0.585	2.139	6.000	—
τ_f^2	0.121	0.354	0.000	0.000	0.006	0.034	0.107	0.480	1.372	—
FDR	0.175	0.188	0.000	0.000	0.025	0.107	0.272	0.577	0.744	—

Table 4: Summary statistics of the 38,740 estimates of the impulse responses induced by a one-unit shock in return and flow innovations. IRF_{ij} represents the response of i to the shock in j. For instance, IRF_{rf} denotes the response of returns to the shock in flow innovations. $I_{ij}(\infty)$ denotes the long-run impact defined in (17).

	Mean	SD	1%	5%	25%	50%	75%	95%	99%
$IRF_{rr}(0)$	1.162	0.139	1.000	1.000	1.045	1.137	1.256	1.417	1.547
$IRF_{rr}(1)$	-0.244	0.129	-0.559	-0.461	-0.327	-0.238	-0.156	-0.045	0.035
$I_{rr}(\infty)$	0.840	0.281	0.335	0.496	0.699	0.831	0.977	1.218	1.398
$IRF_{rf}(0)$	0.998	1.247	0.000	0.000	0.254	0.637	1.284	3.158	6.230
$IRF_{rf}(1)$	0.268	0.468	-0.388	-0.137	0.049	0.168	0.342	1.022	2.270
$I_{rf}(\infty)$	1.392	16.316	0.029	0.175	0.447	0.802	1.543	4.056	8.326
$IRF_{fr}(0)$	0.353	0.277	0.000	0.000	0.162	0.295	0.493	0.879	1.247
$IRF_{fr}(1)$	0.018	0.072	-0.178	-0.096	-0.016	0.019	0.053	0.127	0.221
$I_{fr}(\infty)$	0.375	0.710	-0.219	-0.039	0.172	0.323	0.528	0.984	1.462
$IRF_{ff}(0)$	1.162	0.139	1.000	1.000	1.045	1.137	1.256	1.418	1.547
$IRF_{ff}(1)$	0.052	0.168	-0.470	-0.284	-0.018	0.077	0.151	0.287	0.398
$I_{ff}(\infty)$	1.300	6.770	0.511	0.734	1.054	1.222	1.445	1.854	2.223

Table 5: Regression results with the variables over 15-minute intervals. The first row presents the dependent variables: the price impact b_r, flow impact b_f, difference between the ITH and OLS estimates $\hat{b}_r - b_r$, asymptotic bias δ_{br} defined in (9), and instantaneous impacts $I_{ij}(0)$. I_{ij} represents the response of i to the shock in j. For instance, I_{rf} denotes the flow-to-return impact. Note that $I_{rr}(0) = I_{ff}(0) = 1/(1 - b_r b_f)$. The coefficients of the reciprocal of depth D^{-1} per thousand, number of events NE in millions, average size of events ASE in thousands, average spread SPR, and constant are presented. The coefficients of the 15-minute interval dummies and year dummies are omitted for brevity. N and $\bar{R}^2$ indicate the number of observations and adjusted R-squared values.

	b_r	b_f	$\hat{b}_r - b_r$	δ_{br}	$I_{rr}(0)$	$I_{rf}(0)$	$I_{fr}(0)$
D^{-1}	0.551***	-0.067***	0.542***	0.561***	0.002	0.694***	-0.080***
	(0.017)	(0.004)	(0.019)	(0.019)	(0.002)	(0.022)	(0.005)
NE	-1.482***	-0.068	-0.848***	-0.849***	0.365***	-1.248**	-0.117
	(0.413)	(0.100)	(0.319)	(0.321)	(0.071)	(0.517)	(0.125)
ASE	-3.316***	1.540***	-3.412***	-3.520***	-1.004***	-4.855***	1.311***
	(0.801)	(0.266)	(0.737)	(0.751)	(0.193)	(1.045)	(0.267)
SPR	-7.178**	3.178***	-4.093**	-4.401**	-2.280***	-12.506***	2.777***
	(2.817)	(0.409)	(1.900)	(1.944)	(0.453)	(3.956)	(0.459)
Constant	2.033***	-0.456***	0.965*	1.045**	1.787***	3.389***	-0.271**
	(0.723)	(0.109)	(0.504)	(0.515)	(0.116)	(1.012)	(0.123)
N	38740	38740	38740	38740	38740	38740	38740
$\bar{R}^2$	0.539	0.261	0.564	0.581	0.245	0.541	0.250

Robust standard errors adjusted for 1,490 clusters in date in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Regression results with the variables over five-minute intervals. The first row presents the dependent variables: the standard deviations of return and flow innovations, ω_r and ω_f, conditional variance components driven by return and flow innovations, τ_r^2 and τ_f^2, and FDR, $FDR = \tau_f^2/(\tau_r^2+\tau_f^2)$. The coefficients of the reciprocal of depth D^{-1}, number of events NE in millions, average size of events ASE in thousands, average spread SPR, and constant are presented. The coefficients of the five-minute interval dummies and year dummies are omitted for brevity. N and $\bar{R}^2$ indicate the number of observations and adjusted R-squared values.

	ω_r	ω_f	τ_r^2	τ_f^2	FDR
D^{-1}	0.325***	0.076***	0.272**	0.031	-0.025
	(0.040)	(0.011)	(0.128)	(0.021)	(0.025)
NE	21.256***	7.552***	52.264***	11.330***	-0.885***
	(0.672)	(0.500)	(3.514)	(0.777)	(0.169)
ASE	3.420***	4.211***	12.430***	1.300***	-0.291**
	(0.556)	(0.606)	(3.288)	(0.408)	(0.116)
SPR	13.532***	7.590***	50.006***	6.750***	-0.974***
	(1.907)	(0.815)	(11.361)	(1.482)	(0.291)
Constant	-3.010***	-1.830***	-12.478***	-1.626***	0.464***
	(0.495)	(0.212)	(2.958)	(0.387)	(0.076)
N	116220	116220	116220	116220	116220
$\bar{R}^2$	0.445	0.473	0.175	0.150	0.028

Robust standard errors adjusted for 1,490 clusters in date in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regression results with the announcement dummies over 15-minute intervals. The first row represents the dependent variables: the price impact b_r, flow impact b_f, difference between the ITH and OLS estimates $\hat{b}_r - b_r$, asymptotic bias δ_{br} defined in (9), and instantaneous impacts $I_{ij}(0)$. I_{ij} represents the response of i to the shock in j. For instance, I_{rf} denotes the flow-to-return impact. Note that $I_{rr}(0) = I_{ff}(0) = 1/(1 - b_r b_f)$. The coefficients of the announcement dummy ANN_t, negative-announcement dummy ANN_t^-, and their lags ANN_{t-1} and ANN_{t-1}^- are presented. The coefficients of the other independent variables, reciprocal of depth D^{-1} per thousand, number of events NE in millions, average size of events ASE in thousands, average spread SPR, 15-minute interval and year dummies, and constant are almost identical to those in Table 5 and thus omitted for brevity. N and $\bar{R}^2$ indicate the number of observations and adjusted R-squared values.

	b_r	b_f	$\hat{b}_r - b_r$	δ_{br}	$I_{rr}(0)$	$I_{rf}(0)$	$I_{fr}(0)$
ANN_t	0.020	-0.031**	-0.153***	-0.168***	-0.010	0.004	-0.040***
	(0.043)	(0.013)	(0.038)	(0.039)	(0.008)	(0.052)	(0.014)
ANN_t-1	0.128***	-0.079***	-0.192***	-0.185***	-0.007	0.124**	-0.091***
	(0.042)	(0.012)	(0.040)	(0.041)	(0.008)	(0.048)	(0.013)
ANN_t^-	0.140**	-0.044***	-0.054	-0.061	-0.001	0.180**	-0.049***
	(0.070)	(0.016)	(0.061)	(0.063)	(0.010)	(0.090)	(0.018)
ANN_t-1^-	0.037	-0.013	0.058	0.066	0.004	0.075	-0.013
	(0.067)	(0.015)	(0.054)	(0.055)	(0.011)	(0.082)	(0.017)
N	38740	38740	38740	38740	38740	38740	38740
$\bar{R}^2$	0.539	0.262	0.565	0.581	0.245	0.541	0.252

Robust standard errors adjusted for 1,490 clusters in date in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Regression results with the variables over five-minute intervals. The dependent variables are the standard deviations of return and flow innovations, ω_r and ω_f, conditional variance components driven by return and flow innovations, τ_r^2 and τ_f^2, and FDR, $FDR = \tau_f^2/(\tau_r^2 + \tau_f^2)$. The coefficients of the announcement dummy ANN_t, negative-announcement dummy ANN_t^-, and their lags and forwards are presented. The coefficients of the other independent variables, reciprocal of depth D^{-1}, number of events NE in millions, average size of events ASE in thousands, average spread SPR, five-minute interval and year dummies, constant are almost identical to those in Table 6 and thus omitted for brevity. N and $\bar{R}^2$ indicate the number of observations and adjusted R-squared values.

	ω_r	ω_f	τ_r^2	τ_f^2	FDR
ANN_t	0.093***	-0.047***	0.219*	-0.040	-0.047***
	(0.027)	(0.016)	(0.123)	(0.036)	(0.009)
ANN_{t-1}	0.093***	-0.081***	0.139**	0.013	-0.044***
	(0.017)	(0.010)	(0.060)	(0.023)	(0.010)
ANN_{t-2}	-0.056***	0.002	-0.180***	0.063**	0.073***
	(0.019)	(0.014)	(0.059)	(0.028)	(0.013)
ANN_{t+1}	-0.066***	0.014	-0.251***	0.054	0.056***
	(0.020)	(0.014)	(0.074)	(0.041)	(0.013)
ANN_{t+2}	-0.024	0.009	0.017	0.063**	0.062***
	(0.033)	(0.013)	(0.238)	(0.028)	(0.013)
ANN_t^-	0.003	-0.037	0.098	0.044	0.012
	(0.036)	(0.026)	(0.153)	(0.055)	(0.012)
ANN_{t-1}^-	0.060**	-0.033***	0.192**	-0.003	-0.023*
	(0.024)	(0.013)	(0.084)	(0.026)	(0.013)
ANN_{t-2}^-	0.028	-0.031*	0.079	0.019	-0.016
	(0.028)	(0.019)	(0.079)	(0.048)	(0.019)
ANN_{t+1}^-	-0.012	-0.008	0.014	0.052	0.038**
	(0.027)	(0.023)	(0.093)	(0.054)	(0.018)
ANN_{t+2}^-	-0.033	-0.018	-0.210	0.084*	0.038**
	(0.036)	(0.018)	(0.242)	(0.048)	(0.019)
N	116220	116220	116220	116220	116220
$\bar{R}^2$	0.445	0.474	0.176	0.150	0.030

Robust standard errors adjusted for 1,490 clusters in date in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

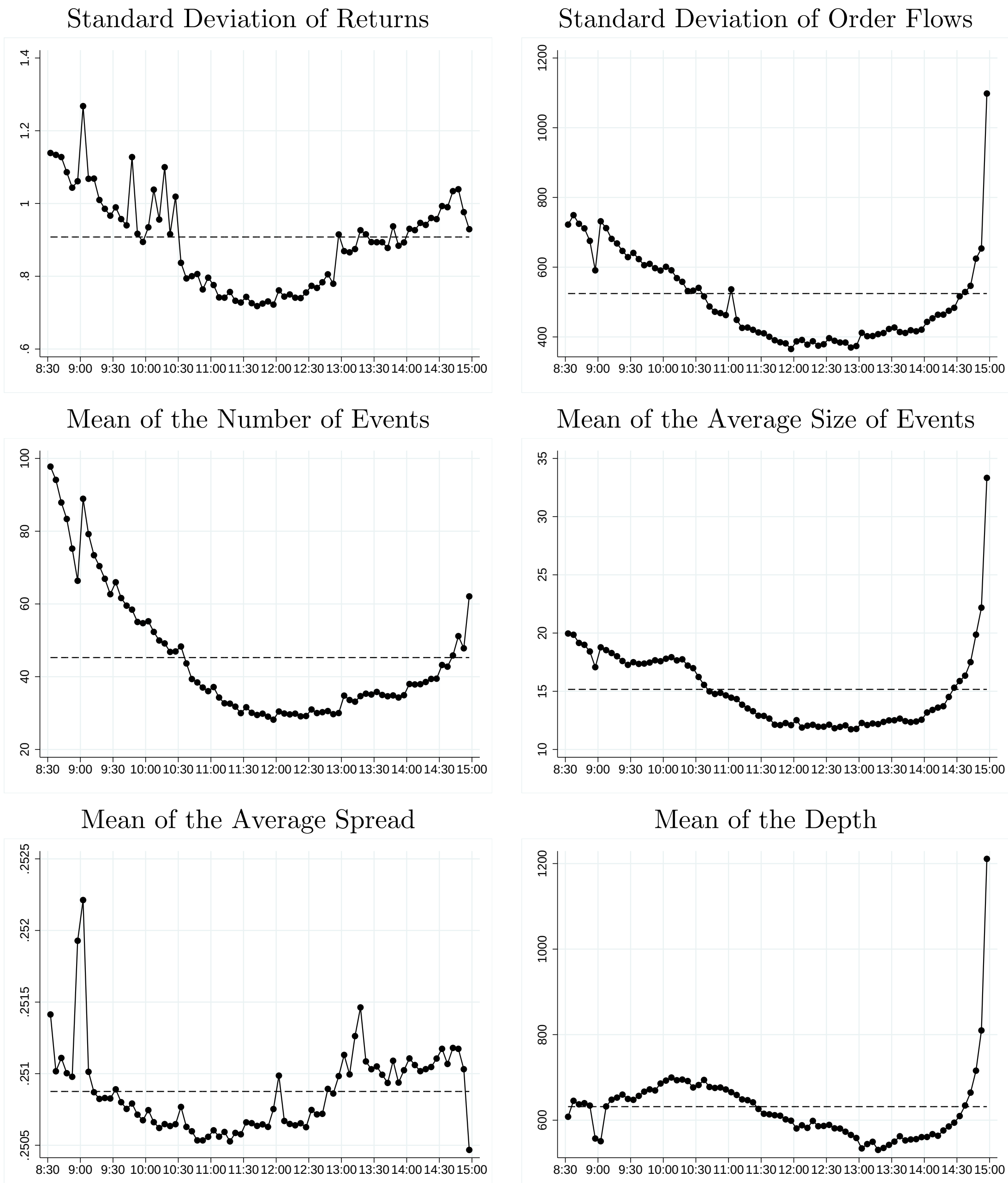

Figure 1: Standard deviations of the mid-quote returns and order flow imbalances and means of the number of events, average size of events, average spread, and depth. The statistics are computed for each five-minute interval from 8:30 until 15:00. The dashed lines indicate the statistics calculated from all samples.

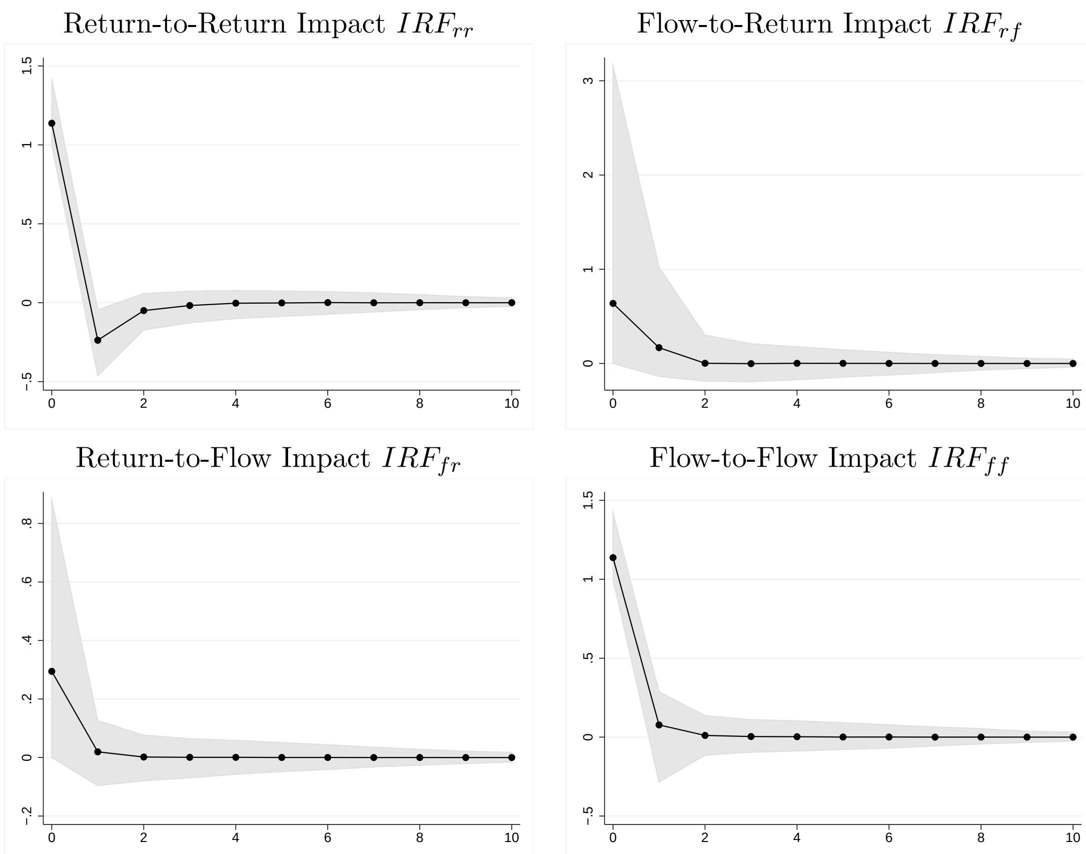

Figure 2: Impulse responses induced by a one-unit shock in return and flow innovations up to 10 lags. IRF_{ij} represents the response of i to the shock in j. For instance, IRF_{rf} denotes the flow-to-return impact. The medians of the 38,740 estimates are presented. The shaded area indicates the 5th and 95th percentiles.

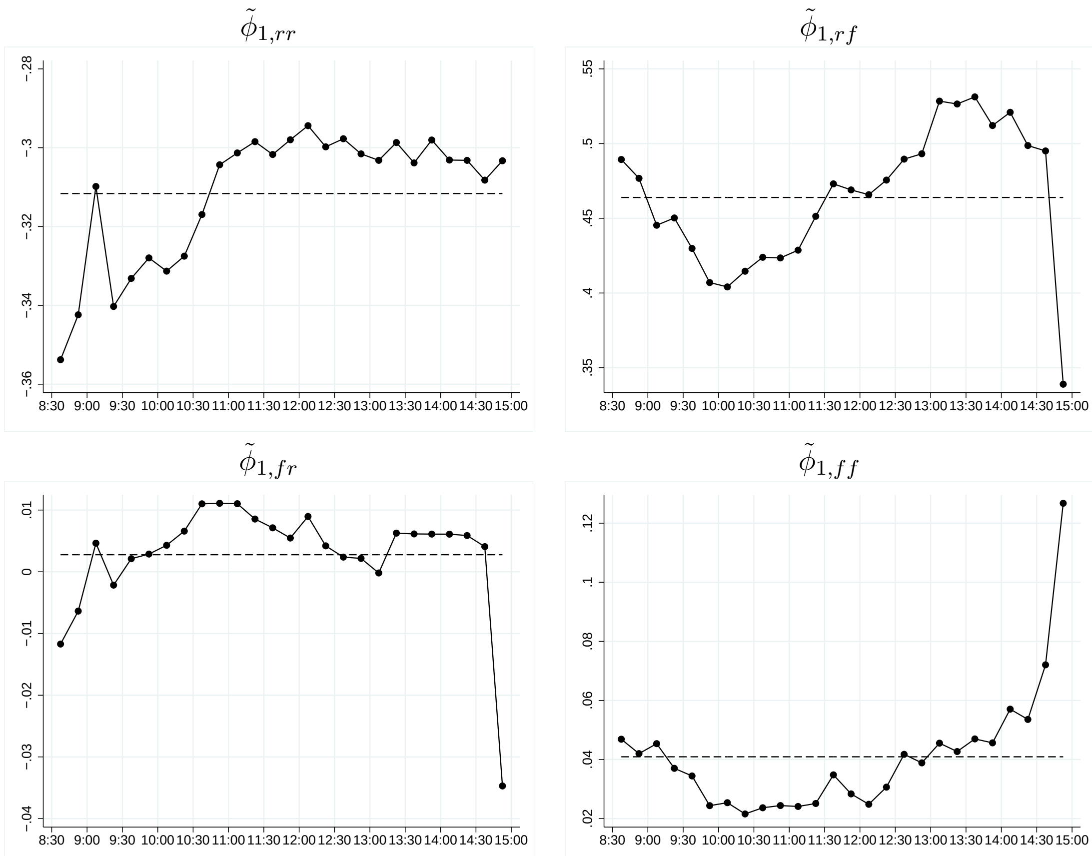

Figure 3: Averages of the 38,740 estimates of the first-order lag coefficients of the reduced-form VAR model (15) for each 15-minute interval from 8:30 until 15:00. $\tilde{\phi}_{1,rr}$, $\tilde{\phi}_{1,rf}$, $\tilde{\phi}_{1,fr}$, and $\tilde{\phi}_{1,ff}$ denote the (1,1), (1,2), (2,1), and (2,2) elements of $\tilde{\Phi}_1$, respectively. The dashed lines indicate the averages over all samples.

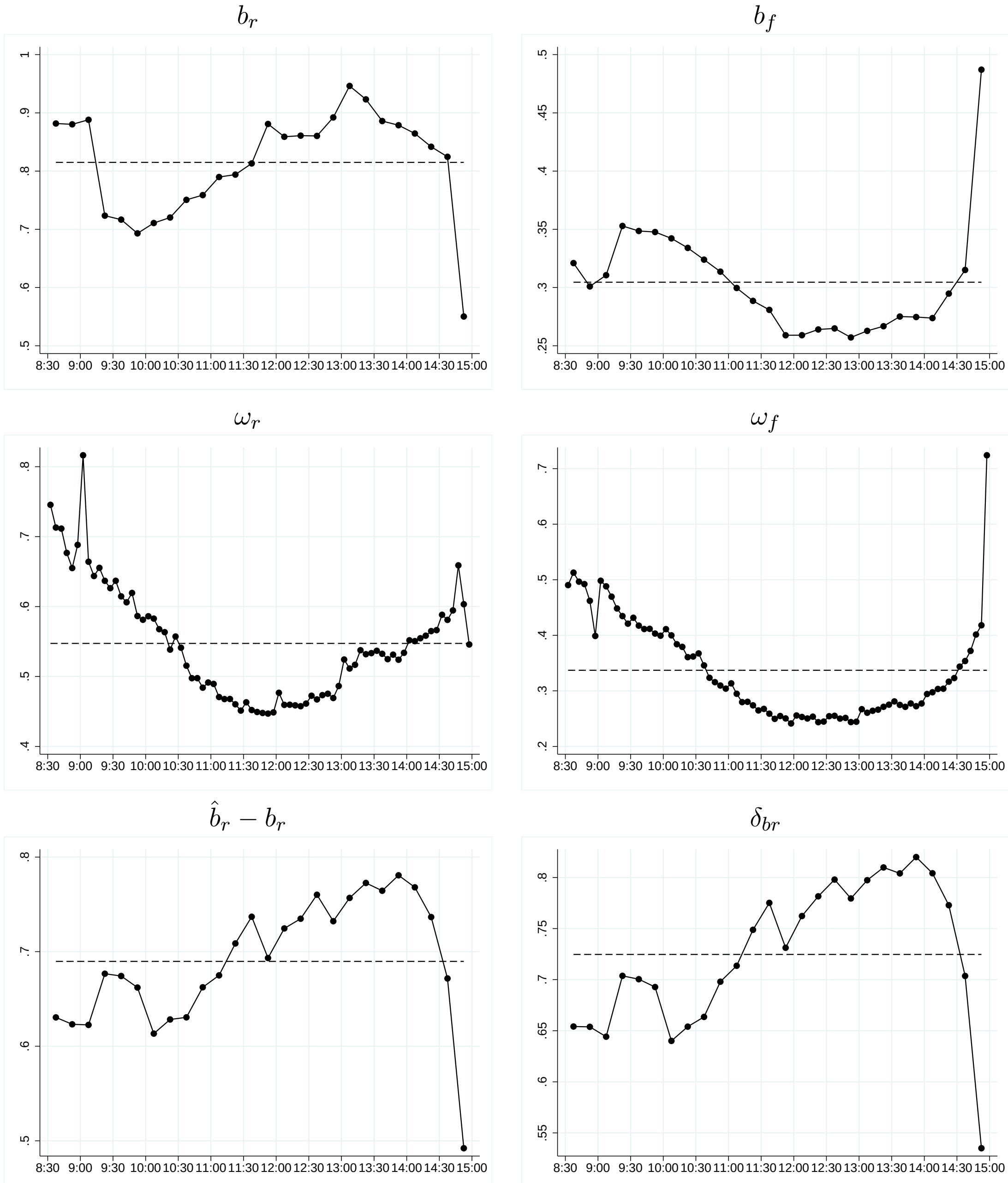

Figure 4: Averages of the 38,740 estimates of the price and flow impacts, b_r and b_f, standard deviations of return and flow innovations, ω_r and ω_f, difference between the OLS and ITH estimates, $\hat{b}_r - b_r$, and asymptotic bias, δ_{br} defined in (9). The averages of b_r, b_f, $\hat{b}_r - b_r$, and δ_{br} are computed for each 15-minute interval, while those of ω_r and ω_f are computed for each five-minute interval. The dashed lines indicate the averages over all samples.

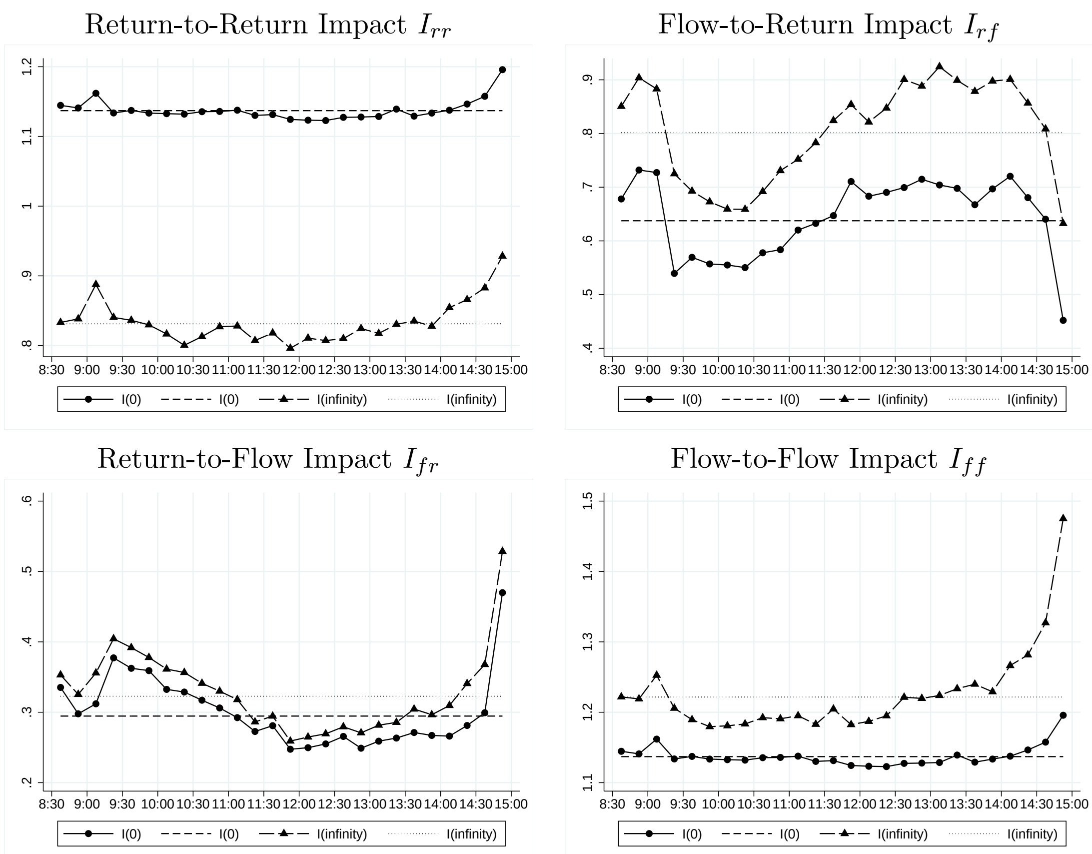

Figure 5: Medians of the 38,740 estimates of the instantaneous and long-run impacts, $I_{ij}(0)$ and $I_{ij}(\infty)$, for each 15-minute interval from 8:30 until 15:00. I_{ij} represents the response of i to the shock in j. For instance, I_{rf} denotes the flow-to-return impact. The dashed and dotted lines indicate the averages over all samples for $I_{ij}(0)$ and $I_{ij}(\infty)$, respectively.

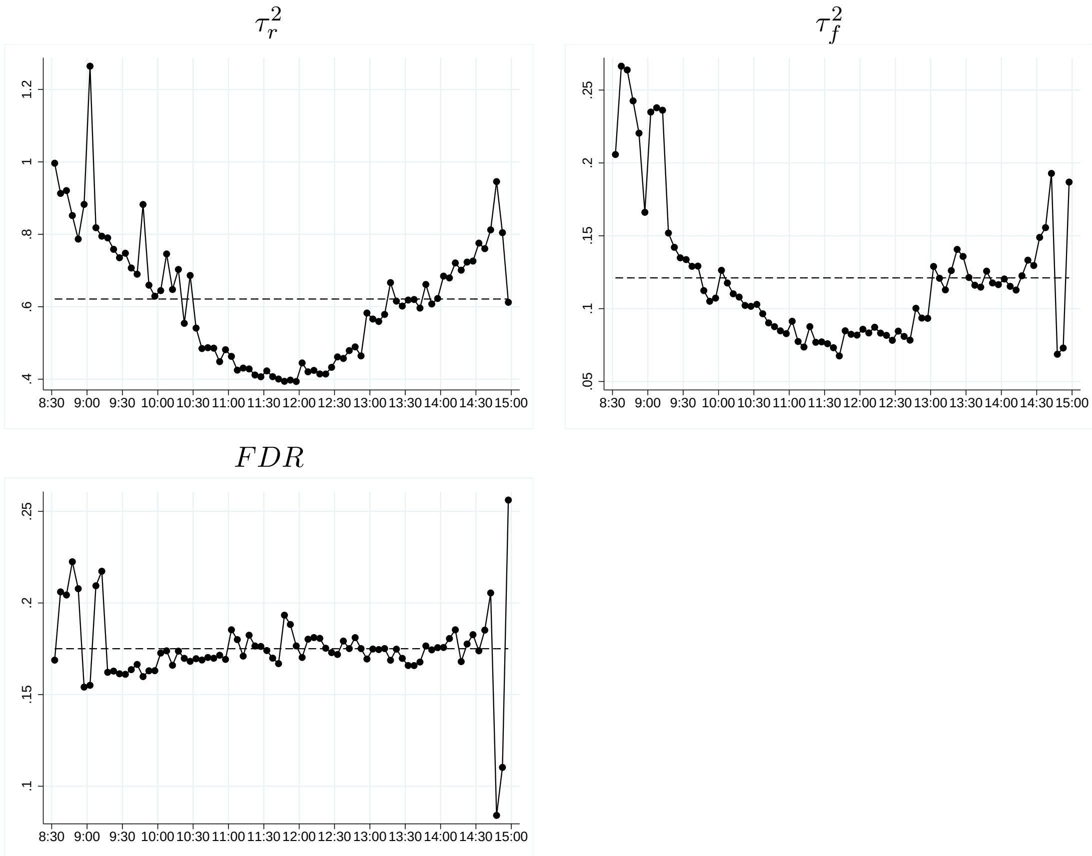

Figure 6: Averages of the 38,740 estimates of the variance components driven by return and flow innovations, τ_r^2 and τ_f^2, and the FDR, FDR, for each five-minute interval from 8:30 until 15:00. The dashed lines indicate the averages over all samples.

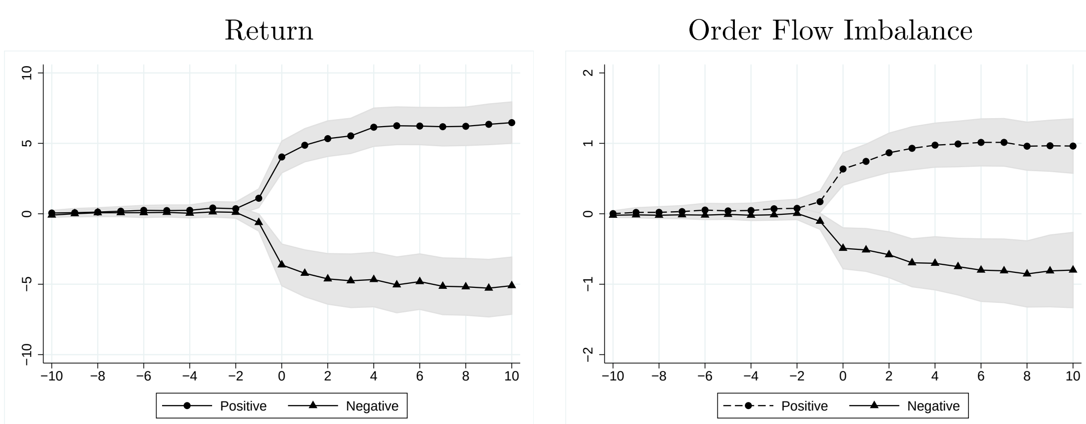

Figure 7: Averages of the cumulative returns and order flow imbalances before and after 10 seconds around positive and negative news announcements. The shaded area represents the 95% interval.