

Returns and Order Flow Imbalances: Intraday Dynamics and Macroeconomic News Effects*

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Abstract

We study the interaction between returns and order flow imbalances in the S&P 500 E-mini futures market using a structural VAR model identified through heteroskedasticity. The model is estimated at one-second frequency for each 15-minute interval, capturing both intraday variation and endogeneity due to time aggregation. We find that macroeconomic news announcements sharply reshape price–flow dynamics: price impact rises, flow impact declines, return volatility spikes, and flow volatility falls. Pooling across days, both price and flow impacts are significant at the one-second horizon, with estimates broadly consistent with stylized limit-order-book predictions. Impulse responses indicate that shocks dissipate almost entirely within a second. Structural parameters and volatilities also exhibit pronounced intraday variation tied to liquidity, trading intensity, and spreads. These results provide new evidence on high-frequency price formation and liquidity, highlighting the role of public information and order submission in shaping market quality.

Keywords: High-frequency data; Identification through heteroskedasticity; Intraday variation; Macroeconomic news; Order flow imbalance; Structural VAR

1 Introduction

Modern electronic markets operate on a limit order book (LOB), a dynamic repository of buy and sell quotes at various price levels.¹ The LOB continuously evolves as new limit orders, market orders, and cancellations arrive. These order flows generate price impact—the immediate change in prices triggered by incoming orders—which reflects the state of market liquidity. Conversely, price changes can in turn trigger further order submissions or

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¹Most financial markets, including major exchanges such as NASDAQ, NYSE, and Euronext, employ electronic LOB systems.

cancellations when traders employ price-contingent strategies. Understanding this two-way interaction between order flows and price changes is fundamental for explaining the price formation mechanism in modern markets.

The market microstructure literature has examined many dimensions of price impact, from the role of trade size and direction to the influence of bid–ask spreads and information asymmetry. A large empirical body also documents intraday patterns in liquidity and trading intensity. While these studies provide valuable insights, they often analyze endogeneity and intraday variation separately rather than within a unified framework. A more comprehensive approach is needed to fully capture how prices and order flows interact in real time. A detailed review of related studies is provided in Section 2.

A closely related line of research is Fleming et al. (2018), who analyze the U.S. Treasury interdealer market on BrokerTec using a vecotre autoregressive (VAR) model of prices and order flow. They show that both trades and limit orders affect prices, and that the variation in limit-order activity makes its contribution to price-update variance especially large; further, macroeconomic announcements amplify these impacts, particularly for limit orders. Our approach complements and extends this evidence. We study a different market—equity index futures—and focus on order flow imbalance (OFI) at the best bid and offer, constructed from one-second BBO data for the S&P 500 E-mini contract. Rather than imposing a recursive VAR, we employ a bivariate structural VAR identified through heteroskedasticity (SVAR–ITH), which allows us to disentangle the contemporaneous price impact of OFI from the reverse flow impact of returns. By re-estimating the system across short intraday intervals, we trace the within-day dynamics of these impacts and show how they respond to macroeconomic news releases.

Our contributions are threefold. First, we provide an integrated framework that simultaneously addresses endogeneity and intraday variation—two central features of high-frequency markets that prior studies have largely examined separately. Second, we document pronounced within-day variation in both price and flow impacts, linking them to liquidity conditions and order submission behavior. Third, we demonstrate that macroeconomic news announcements systematically reshape the return–flow relationship, temporarily raising price impact and dampening flow impact, with implications for trading strategies and liquidity provision.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 describes the dataset and variable construction. Section 4 presents the SVAR framework and estimation methodology. Section 5 reports the empirical findings. Finally, Section 6 concludes.

2 Related Literature

The interaction between order flows and price changes has been a central theme in market microstructure research, spanning several strands of the literature.

A first strand examines the price impact of trades and orders. Since Hasbrouck (1991), VAR models have been widely used to show that trades convey information and exert a lasting influence on prices. This empirical tradition builds on asymmetric information models such as Bagehot (1971), Kyle (1985), and Glosten and Milgrom (1985).

A second strand focuses on the structure of the LOB. Bouchaud et al. (2002, 2004, 2006) documented stylized facts such as the concavity of the price impact function and the long memory of order signs. Cont et al. (2014) developed a stylized model linking order flow imbalance to short-horizon price changes, and showed that estimated price impact varies systematically across the day.²

²Market activity is well known to follow a U-shaped intraday pattern, with high activity at the open, a midday trough, and renewed activity into the close; see Wood et al. (1985), McInish and Wood (1992), and Andersen and Bollerslev (1997).

A third strand highlights the simultaneity of prices and order flows. Because traders often employ price-contingent strategies, the two are jointly determined. Deuskar and Johnson (2011) addressed this endogeneity using the ITH approach of Rigobon (2003) and its extensions, showing that ignoring simultaneity biases price impact estimates and masks important variation in liquidity conditions.

Our study contributes to all three strands by combining insights from the VAR tradition, the LOB literature, and ITH-based identification into a unified framework. Using one-second data, we explicitly capture both the intraday variation in market activity and the bidirectional causality between prices and order flows.

3 Data and Variable Construction

3.1 Market and Dataset Overview

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.³ The BBO file records all events that change the price or size of the best bid and ask quotes, including transactions from marketable orders and quote revisions from limit orders and cancellations. Each event is time-stamped to the second with a unique sequence number for the day.

The sample covers 1,490 trading days from January 2, 2008 to December 31, 2013.⁴ For each day, we extract observations from 8:30–15:00 Chicago Time, corresponding to NYSE regular trading hours when most S&P 500 components trade. To ensure data consistency, we select the most active contract (highest daily trading volume) each day.⁵

3.2 Variable Construction

From the BBO data, mid-quote returns, denoted by r_t , are computed every second. Order flow imbalances (OFI) are constructed following Cont et al. (2014). Let P_n^a and q_n^a denote the best ask price and size, and P_n^b and q_n^b the best bid price and size. The order book event is defined as:

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

where $I_{\{A\}}$ is an indicator function. Aggregating e_n over one-second intervals yields the order flow imbalance f_t .⁶

We also compute additional market activity measures:

- Number of order book events and average size of events (order activity and aggressiveness)
- Average spread (transaction cost proxy)

³The 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 nearly 24 hours from Monday to Friday. 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.

⁴Days with insufficient observations—mostly before/after holidays—are excluded.

⁵The most active contract typically rolls from the front month to the next about a week before the expiry.

⁶If order types are available, OFI can alternatively be computed by summing market, limit, and cancellation orders on both sides.

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 (1). 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

- Depth, calculated as the average of bid and ask sizes around price changes:

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

where I_t represents a one-second interval.

3.3 Summary Statistics

Table 1 presents summary statistics for mid-quote returns, OFI, and market activity variables. Both returns and OFI are roughly symmetric around zero but highly variable. OFI percentiles reveal periods with intense one-sided order submission. On average, 45 events occur per second, each averaging 15 contracts. While the spread remains at the minimum tick size (0.25), depth is substantial compared with event size.

These statistics confirm that the E-mini market is highly liquid and active, with multiple events per second—raising potential endogeneity concerns if returns and flows are aggregated.

3.4 Intraday Variations

Figure 1 illustrates the intraday patterns of return and OFI volatilities, as well as various market activity measures. The standard deviations of returns and OFI, as well as the number and size of events, exhibit the familiar U-shaped pattern, with heightened activity at the open and close.⁷

Notably:

- In the last 5 minutes (14:55–15:00), OFI volatility, event size, and depth rise sharply, while return volatility and spread decline—consistent with high liquidity.
- Around 9:00, return volatility and spreads spike while order activity drops, reflecting temporary illiquidity.

These patterns underscore the importance of accounting for intraday variation when modeling the return–order flow interaction (Section 4). From a practical perspective, these shifts in market conditions imply that high-frequency traders, liquidity providers, and algorithmic strategies face very different execution environments across

⁷See footnote 2 for prior literature on U- and J-shaped intraday patterns.

Standard Deviation of Returns

Standard Deviation of Order Flows

Mean of the Number of Events

Mean of the Average Size of Events

Mean of the Average Spread

Mean of the Depth

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.

the day. Ignoring such variation can lead to misestimation of price impact and potentially suboptimal trading or risk management decisions.

4 Methodology

This section outlines the model and estimation framework used to examine the interaction between asset returns and order flow imbalances. The analysis builds on the simultaneous equations framework of Deuskar and Johnson (2011). First, a simple bivariate model is introduced to illustrate the endogeneity problem. Second, the ITH method is described under a simplified setting. Finally, a SVAR model is presented, which incorporates both endogeneity and the dynamic interaction between returns and flows, and we define measures of instantaneous and long-run impacts. For brevity, the term “order flows” is used interchangeably with “order flow imbalances” in what follows.

4.1 Simple Bivariate Model

The contemporaneous impact of order flows on returns is captured by the following equation:

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

where r_t and f_t denote 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 interpreted as the *price impact* of order flows, reflecting market illiquidity. A larger b_r implies greater sensitivity of returns to order flows and therefore lower liquidity, whereas $b_r = 0$ indicates a perfectly liquid market.

At ultra-high frequencies, the price impact of an individual order is largely mechanical, depending on the depth of the LOB. Under the stylized LOB model of Cont et al. (2014), the price impact is approximately $1/2D$, where D is the market depth. Using NYSE Trades and Quotes data, Cont et al. (2014) verify that the price impact of aggregated order flow imbalances is consistent with this stylized model.

In practice, however, returns and flows are measured over short intervals that contain many orders. This aggregation introduces *endogeneity*, since price changes can trigger further order submissions within the same interval. Deuskar and Johnson (2011) trace this simultaneity to stale limit orders and price-contingent trading strategies discussed by Obizhaeva (2008) and Obizhaeva and Wang (2013). Accounting for this endogeneity requires an additional equation for order flows:

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

where $\epsilon_{f,t}$ is an innovation in flows, with mean zero and variance ω_f^2 , assumed uncorrelated with $\epsilon_{r,s}$ for any s . The coefficient b_f measures the *flow impact*, i.e., the feedback from returns to concurrent order flows, and should be zero if no endogeneity exists.

The two equations can be summarized in matrix form:

$$By_t = \epsilon_t, \quad \epsilon_t \sim (0, \Omega), \quad (3)$$

where $y_t = (r_t, f_t)'$, $\epsilon_t = (\epsilon_{r,t}, \epsilon_{f,t})'$, and

$$B = \begin{pmatrix} 1 & -b_r \\ -b_f & 1 \end{pmatrix}, \quad \Omega = \begin{pmatrix} \omega_r^2 & 0 \\ 0 & \omega_f^2 \end{pmatrix}. \quad (4)$$

This implies $y_t = B^{-1}\epsilon_t$, where B^{-1} is non-diagonal, meaning f_t and $\epsilon_{r,t}$ are correlated. As a result, OLS applied to (2) produces an inconsistent estimator of b_r when $b_f \neq 0$. To obtain consistent estimates, we adopt the ITH method described below.

4.2 ITH Method

Let Σ denote the variance–covariance matrix of y_t :

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

From (3), the relationship $B\Sigma B' = \Omega$ holds, which yields three equations:

$$\sigma_r^2 - 2b_r\sigma_{rf} + b_r^2\sigma_f^2 - \omega_r^2 = 0, \quad (5)$$

$$\sigma_f^2 - 2b_f\sigma_{rf} + b_f^2\sigma_r^2 - \omega_f^2 = 0,$$

$$b_f\sigma_r^2 - (1 + b_r b_f)\sigma_{rf} + b_r\sigma_f^2 = 0. \quad (6)$$

The sample variances and covariance provide estimates of σ_r^2 , σ_f^2 , and σ_{rf} . However, the system contains four unknowns ($b_r, b_f, \omega_r, \omega_f$) but only three equations, so identification fails without further restrictions.

The ITH method resolves this by exploiting heteroskedasticity. Suppose there are S states such that the variance–covariance matrix Σ changes across states, while b_r and b_f in B remain constant. For each state $s = 1, \dots, S$, equations (5)–(6) hold, with $\omega_{r,s}$ and $\omega_{f,s}$ varying by state.

With S states, there are $3S$ equations and $2 + 2S$ unknowns. If $S \geq 2$ (order condition) and the following rank condition holds for any $s' \neq s''$,

$$\sigma_{r,s'}^2\sigma_{rf,s''} - \sigma_{r,s''}^2\sigma_{rf,s'} \neq 0, \quad (7)$$

the parameters are identified.⁸ Under these conditions, the parameters can be estimated by the generalized method of moments (GMM) using the $3S$ moment conditions implied by (5)–(6).

Deuskar and Johnson (2011) estimate this bivariate model assuming b_r and b_f are constant, while ω_r^2 and ω_f^2 vary across the day. They find both b_r and b_f are significantly positive, confirming endogeneity in flows and the resulting simultaneity bias in price impact estimates.

4.3 SVAR Model

The simple bivariate model (3) addresses endogeneity but ignores the serial dependence of returns and flows. To account for both endogeneity and dynamic interaction, we extend it to a SVAR:

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

where B and Ω are as in (4) and Φ_j are 2×2 matrices capturing autocorrelation.

The SVAR can be rewritten in reduced form:

$$y_t = \tilde{c} + \tilde{\Phi}_1 y_{t-1} + \tilde{\Phi}_2 y_{t-2} + \dots + \tilde{\Phi}_p y_{t-p} + \eta_t, \quad (8)$$

⁸See Rigobon (2003) for details on estimation and identification in general settings.

where $\tilde{c} = B^{-1}c$, $\tilde{\Phi}_j = B^{-1}\Phi_j$, and $\eta_t = B^{-1}\epsilon_t$. The residuals $\hat{\eta}_t$ from the reduced-form VAR provide inputs to the ITH estimation, which yields estimates of b_r , b_f , and the standard deviations ω_r and ω_f .

Once the SVAR is identified, impulse response functions (IRFs) trace the effects of shocks. Let $IRF_{ij}(k)$ denote the response of variable i to a one-unit shock in innovation j at horizon k , where $i, j \in \{r, f\}$. For example, $IRF_{rf}(k)$ measures the impact of order flow shocks on returns at lag k . The cumulative response up to horizon K is:

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

The *instantaneous impact* is $I_{ij}(0) = IRF_{ij}(0)$. The *long-run impact* is defined as

$$I_{ij}(\infty) = \sum_{k=0}^{\infty} IRF_{ij}(k) = \left[(I_2 - \tilde{\Phi}_1 - \tilde{\Phi}_2 - \cdots - \tilde{\Phi}_p)^{-1} B^{-1} \right]_{ij}, \quad (9)$$

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

5 Empirical Results

This section presents the main empirical findings from the SVAR model estimated using one-second BBO data for the S&P 500 E-mini futures contract. The model is estimated separately for each 15-minute interval of each trading day, allowing us to capture time variation in structural parameters and impulse responses. We first highlight the effects of macroeconomic news announcements, as they represent the most pronounced source of variation in the return–flow relationship. We then present the estimation results for structural parameters and innovation volatilities, followed by impulse response functions, and finally discuss intraday patterns.

5.1 Macroeconomic News Effects

Macroeconomic announcements are a key source of public information that sharply alters trading activity, liquidity, and the relationship between prices and order flows. Prior research such as Andersen et al. (2003, 2007) and Hautsch et al. (2011) shows that these announcements trigger intense trading and spikes in return volatility, while Brogaard et al. (2014) demonstrate that high-frequency traders actively adjust their strategies in response. Building on this literature, we investigate how major U.S. macroeconomic releases shape the structural parameters estimated in our SVAR model.

We focus on the eight announcements analyzed by Brogaard et al. (2014): construction spending, consumer confidence, existing home sales, factory orders, ISM manufacturing, ISM services, leading indicators, and wholesale inventories. Most of these announcements are released at 9:00 Chicago Time.⁹

Figure 2 compares the average estimates of key structural parameters (b_r , b_f , ω_r , and ω_f) and market activity variables (D^{-1} and SPR) on days with and without a 9:00 announcement. Several patterns emerge:

- **Price impact (b_r) rises sharply around 9:00 on announcement days.** This means that a given order flow imbalance moves prices more when news is released, consistent with liquidity deterioration reflected in higher D^{-1} and wider spreads (SPR).

⁹Exceptions include ISM services (7:55 on February 5, 2008 and 10:00 on August 5, 2008) and consumer confidence (8:37 on June 28, 2011).

- **Flow impact (b_f) drops around 9:00.** Order flows become less sensitive to price changes, indicating that traders pull back from price-contingent strategies before and immediately after announcements.
- **Return innovation volatility (ω_r) spikes just after announcements.** In the 9:00–9:05 window, ω_r is markedly higher, reflecting abrupt price adjustments to newly released information.
- **Flow innovation volatility (ω_f) declines before announcements.** In the 8:55–9:00 interval, ω_f falls as traders temporarily refrain from submitting orders in anticipation of news.

To formalize these patterns, we estimate regressions with two announcement dummies. The first, ANN_t , equals one if any of the eight announcements are released in interval t ; the second, ANN_t^- , equals one if the announced value falls below the consensus forecast. Leads and lags of these dummies are included to capture pre- and post-announcement effects. Regressions are run separately for parameters computed over 15-minute intervals (b_r and b_f) and over 5-minute intervals (ω_r and ω_f), with controls for market activity variables—the reciprocal of depth D^{-1} defined in (1), the number of order book events NE , the average size of events ASE , and the average spread SPR —as well as time dummies.

Table 2 presents the results. The key findings are:

- **Price impact (b_r):** The coefficient on ANN_{t-1} is significantly positive, indicating that price impact rises just before announcements as traders withdraw liquidity. ANN_t^- is also significantly positive, showing that negative news further amplifies price impact.
- **Flow impact (b_f):** Coefficients on ANN_t and ANN_{t-1} are significantly negative, consistent with order flows becoming less responsive to prices before and after announcements. ANN_t^- is likewise significantly negative, implying that negative announcements further reduce flow responsiveness.
- **Return volatility (ω_r):** ANN_t is significantly positive, while ANN_{t-2} and ANN_{t+1} are significantly negative, indicating a volatility spike at release followed by a gradual decline.
- **Flow volatility (ω_f):** ANN_t and ANN_{t-1} are significantly negative, confirming that traders reduce order submissions before and around announcements.

Overall, macroeconomic announcements significantly reshape the price–flow dynamic: liquidity tightens, price impact intensifies, and order submission slows. Although the announcement dummies are statistically significant, the adjusted R^2 values change little when they are included, suggesting that much of the observed variation is already captured by market activity variables reflecting public information.

5.2 Structural Parameters

The reduced-form VAR model (8) is estimated using returns r_t and order flow imbalances f_t over one-second intervals, separately for each 15-minute interval and each day. This results in 38,740 estimations.¹⁰ The variance–covariance matrices of the residuals are then used to check the rank condition (7), leaving 37,029 intervals suitable for ITH estimation.

¹⁰The number of lags p chosen by the Akaike information criterion is positive in 38,725 intervals. On average, lagged returns explain 8.7% of the variation in returns and lagged flows explain 4.6% of the variation in flows, with R^2 values occasionally exceeding 20%. These findings confirm strong auto- and cross-correlation structures, motivating the SVAR framework.

b_r b_f ω_r ω_f D^{-1} SPR

Figure 2: Average values of structural parameters (b_r , b_f , ω_r , and ω_f) and market activity variables (D^{-1} and SPR) on days with macroeconomic announcements released at 9:00 Chicago Time (black circles, solid line) and on days without announcements (gray triangles, dashed line). Estimates of b_r and b_f are averaged over 15-minute intervals, while the other variables are averaged over five-minute intervals.

Table 2: Regression results with the announcement dummies. The dependent variables are the price impact (b_r), flow impact (b_f), return innovation volatility (ω_r), and flow innovation volatility (ω_f). The coefficients of the announcement dummy ANN_t , negative-announcement dummy ANN_t^- , and their leads and lags, if significant, are reported. The coefficients of the other independent variables are almost identical to those in Table 5 and are omitted for brevity. \bar{R}^2 indicates the adjusted R-squared value. Robust standard errors adjusted for 1,490 clusters in date in parentheses.

	b_r	b_f	ω_r	ω_f
ANN_t	0.025 (0.043)	-0.033** (0.013)	0.066*** (0.018)	-0.039** (0.016)
ANN_{t-1}	0.129*** (0.042)	-0.078*** (0.012)	-0.014 (0.014)	-0.057*** (0.009)
ANN_{t-2}			-0.040*** (0.014)	-0.004 (0.014)
ANN_{t+1}			-0.032** (0.014)	0.006 (0.014)
ANN_t^-	0.136* (0.070)	-0.043*** (0.016)	-0.039 (0.026)	-0.026 (0.025)
ANN_{t+1}^-			-0.042** (0.019)	0.000 (0.023)
ANN_{t+2}^-			-0.067** (0.032)	-0.009 (0.018)
\bar{R}^2	0.541	0.269	0.681	0.510

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

Table 3: Estimation results of the structural parameters in (4). For each 15-minute interval satisfying the rank condition (7), 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 37,029 estimations. 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.

	Mean	SD	1%	5%	25%	50%	75%	95%	99%	*
b_r	0.834	0.999	0.000	0.000	0.242	0.556	1.065	2.576	4.950	0.64
b_f	0.301	0.242	0.000	0.000	0.133	0.246	0.419	0.772	1.088	0.71
$\omega_{r,1}$	0.574	0.408	0.123	0.198	0.335	0.475	0.682	1.282	2.135	0.98
$\omega_{r,2}$	0.554	0.382	0.121	0.191	0.326	0.463	0.659	1.227	2.049	0.98
$\omega_{r,3}$	0.552	0.393	0.122	0.192	0.324	0.459	0.654	1.227	2.069	0.98
$\omega_{f,1}$	0.344	0.242	0.068	0.105	0.188	0.280	0.424	0.814	1.223	0.96
$\omega_{f,2}$	0.339	0.234	0.068	0.104	0.186	0.278	0.419	0.788	1.228	0.96
$\omega_{f,3}$	0.344	0.245	0.066	0.102	0.185	0.278	0.425	0.814	1.252	0.96

For each valid interval, the ITH method is applied to estimate the structural parameters in (4). The price and flow impacts (b_r, b_f) are assumed constant within a 15-minute window, while the standard deviations of return and flow innovations (ω_r, ω_f) vary across three nested five-minute subintervals. This yields one set of (b_r, b_f) and three sets of (ω_r, ω_f) for each 15-minute block. Because three heteroskedastic states are used, the system is over-identified.

Table 3 summarizes these results. The estimated price impact b_r exhibits substantial variation, from nearly zero to almost five, and is statistically significant in 64% of intervals. The mean value (0.834) is considerably larger than the conditional impact of 0.474 reported by Deuskar and Johnson (2011), who used one-minute data. This suggests that shorter sampling intervals capture stronger contemporaneous impacts of order flow on prices.

By contrast, the flow impact b_f is more moderate, typically between zero and one, but remains significant in 71% of intervals. The average value (0.301) is lower than the 0.55 reported by Deuskar and Johnson (2011), consistent with the idea that endogeneity weakens as the measurement interval approaches the event level.

The innovation volatilities ω_r and ω_f are highly significant in over 96% of intervals. ω_r is consistently larger than ω_f , reflecting the higher variability of returns relative to flows. These volatilities also display pronounced intraday variation, as documented earlier in Section 3.

5.3 Impulse Responses

Having identified the structural parameters, we now analyze the dynamic interactions between returns and flows. Figure 3 shows the median impulse responses of returns and flows to shocks, along with 5th and 95th percentiles, computed from the 37,029 estimations.

Several patterns emerge. First, most impacts dissipate quickly, with responses beyond one lag nearly negligible. This implies that market adjustments to order flow and return shocks occur within a second, consistent with Hautsch and Huang (2012), who report that quotes reach new levels after roughly 20 events—less than the average number of events in one second in our sample.

The instantaneous responses $IRF_{ij}(0)$ are almost uniformly positive, confirming significant contemporaneous

Return-to-Return Impact IRF_{rr} Flow-to-Return Impact IRF_{rf}

Return-to-Flow Impact IRF_{fr} Flow-to-Flow Impact IRF_{ff}

Figure 3: 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 . The medians of the 37,029 estimates are presented. The shaded area indicates the 5th and 95th percentiles.

interactions between return and flow shocks. The first-lag return-to-return response $IRF_{rr}(1)$ is negative in over 95% of cases, suggesting short-term reversal in returns. Other first-lag responses fluctuate around zero with no consistent sign.

Table 4 reports summary statistics of the long-run impacts $I_{ij}(\infty)$ defined in (9). All are positive on average except for $I_{fr}(\infty)$ in some intervals. A one-unit flow shock, corresponding to an unexpected increase of about 1,000 contracts at the best bid or ask, raises prices by roughly 1.42 basis points in the long run. Using the mean flow volatility ω_f (0.34, about half the mean depth in Table 1), this translates into a price impact of 0.48 basis points—closely aligned with the 0.5–0.6 basis points reported by Hautsch and Huang (2012) for limit orders of half-depth.

Taken together, these results show that while return–flow interactions are strong at the contemporaneous level, they dissipate extremely rapidly. The long-run effects of flow shocks are economically meaningful and consistent with established findings in the market microstructure literature.

Table 4: Summary statistics of the 37,029 estimates of the long-run impacts $I_{ij}(\infty)$ defined in (9).

	Mean	SD	1%	5%	25%	50%	75%	95%	99%
$I_{rr}(\infty)$	0.843	0.283	0.338	0.499	0.702	0.834	0.980	1.220	1.399
$I_{rf}(\infty)$	1.423	16.688	0.038	0.180	0.454	0.817	1.580	4.122	8.464
$I_{fr}(\infty)$	0.372	0.721	-0.212	-0.037	0.171	0.320	0.523	0.977	1.455
$I_{ff}(\infty)$	1.304	6.925	0.514	0.735	1.056	1.224	1.448	1.861	2.226

5.4 Intraday Variations

We next examine how the structural parameters and innovation volatilities evolve within the trading day. Figure 4 plots the averages of b_r , b_f , ω_r , and ω_f across 15-minute or 5-minute intervals, respectively.

The estimated price impact b_r is elevated in the opening interval (8:30–9:15), drops around 9:15–9:30, and then gradually rises over the trading session, peaking around 13:00–13:15 before declining sharply into the close. By contrast, the flow impact b_f increases in 9:00–9:30, declines steadily until midday, reaches its lowest point around 12:45–13:00, and then surges in the final interval (14:45–15:00). This pattern suggests that returns are least sensitive to flows in the late afternoon, while flows become increasingly driven by returns toward the close, consistent with heightened liquidity and trading activity during that period (see Figure 1).

The standard deviations of return and flow innovations, ω_r and ω_f , mirror the volatility dynamics of returns and order flow imbalances, respectively. Notably, ω_r spikes in 9:00–9:05, while ω_f falls in 8:55–9:00, patterns linked to macroeconomic announcements as shown in Section 5.1. In addition, ω_f rises sharply in the last five minutes (14:55–15:00), reflecting aggressive order submission near the close.

To investigate the drivers of these patterns, we regress the estimated parameters on market activity measures. Table 5 reports the results. For b_r , the coefficient on reciprocal depth (D^{-1}) is strongly positive, confirming that order flows exert larger price impacts when the market is thin. This estimate is close to the theoretical benchmark implied by the stylized LOB model of Cont et al. (2014). By contrast, *NE* (number of events) and *ASE* (average size of events) both enter negatively, indicating that more active and aggressive order submissions reduce the contemporaneous price impact. A wider spread (*SPR*) also lowers b_r . Together with time dummies, these variables explain about 54% of the variation in b_r .

For b_f , the coefficients on D^{-1} and *SPR* are significantly negative and positive, respectively, implying that returns induce more order flow imbalances when the market is thin or trading costs are high. *ASE* enters positively, showing that flows are more sensitive to returns when order submissions are aggressive. The explanatory power (27%) is about half that for b_r , consistent with the idea that additional factors govern return-induced flows.

Turning to innovation volatilities, ω_r rises with illiquidity (D^{-1}), while ω_f falls, indicating that thin markets amplify return shocks but dampen flow shocks. Both measures increase with more active (*NE*) and aggressive (*ASE*) order submissions, as well as with wider spreads. These variables account for 68% and 51% of the variation in ω_r and ω_f , respectively.

Overall, these results show that intraday fluctuations in structural parameters are closely tied to liquidity and trading activity. Combined with the announcement effects documented in Section 5.1, they underscore how both public information releases and market microstructure conditions shape the dynamics between order flows and

b_r b_f ω_r ω_f

Figure 4: Intraday averages of estimated price and flow impacts (b_r, b_f) and standard deviations of return and flow innovations (ω_r, ω_f). The averages of b_r and b_f are computed for each 15-minute interval; those of ω_r and ω_f are computed for each five-minute interval. Dashed lines indicate full-sample averages.

Table 5: Regression results for intraday variations. Dependent variables are structural parameters (b_r, b_f) estimated over 15-minute intervals and innovation volatilities (ω_r, ω_f) estimated over five-minute intervals. Explanatory variables are reciprocal depth D^{-1} (per thousand), number of events NE (in millions), average size of events ASE (in thousands), and average spread SPR , plus time dummies. Robust standard errors are clustered by date.

	b_r	b_f	ω_r	ω_f
D^{-1}	0.553*** (0.017)	-0.066*** (0.004)	0.204*** (0.007)	-0.049*** (0.002)
NE	-1.628*** (0.429)	0.009 (0.095)	12.357*** (0.434)	9.423*** (0.449)
ASE	-3.421*** (0.834)	1.502*** (0.266)	1.799*** (0.279)	4.471*** (0.640)
SPR	-7.510*** (2.868)	3.173*** (0.413)	7.302*** (0.732)	8.833*** (0.914)
\bar{R}^2	0.541	0.268	0.681	0.509

Robust standard errors adjusted for 1,490 date clusters.

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

returns throughout the trading day.

6 Conclusion

This paper examines the interaction between returns and order flow imbalances in the S&P 500 E-mini futures market using a structural VAR identified through heteroskedasticity. By estimating the model at the one-second frequency and separately for each 15-minute interval, we capture both intraday variation and the endogeneity between prices and flows.

The empirical analysis yields several insights. Macroeconomic news announcements sharply alter high-frequency dynamics: price impact rises, flow impact declines, return volatility spikes, and flow volatility falls, reflecting temporary liquidity withdrawal. Beyond announcements, structural linkages between returns and flows remain economically significant at the one-second horizon. Price impact estimates are consistent with stylized LOB models, while flow impact confirms feedback from prices to order submissions. Impulse response analysis shows that shocks dissipate within a second, highlighting the efficiency of high-frequency price discovery. Finally, strong intraday patterns in impacts and volatilities are closely tied to market activity measures such as depth, order frequency, and spreads.

Overall, the results underscore how liquidity provision and order submission adapt to scheduled announcements and intraday conditions, offering new evidence on the microstructure of modern electronic markets. Future work could extend the framework to multivariate settings that distinguish order types or explore cross-market interactions between related assets.

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