〔Research Note〕

Price Impact of Order Flow Imbalances

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Abstract

The study examines the price impact of order flow imbalances (differences between buy and sell orders), constructed from the order book data of Amazon.com, Inc., using the price impact model introduced by Cont et al. (2014). In contrast to Cont et al. (2014), the estimation results suggest the nonlinear or concave relation between price changes and order flow imbalances. Nevertheless, the intraday pattern of the estimated price impact is roughly similar to Cont et al. (2014). That is, the price impact is high around the time the market opens but small around its close. On the other hand, the quadratic price impact shows the exact opposite intraday pattern, suggesting that the nonlinear or concave relation between price changes and order flow imbalances is especially evident after the market opens.

Keywords: High frequency data; Intraday variation; Order flow imbalance; Price impact.

1 Introduction

Modern electronic trading is implemented with a limit order book, which is a collection of quotes at various price levels (most financial markets, including leading exchanges such as the NASDAQ, the NYSE, and Euronext, employ electronic limit order book systems). The limit order book 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 order book data of Amazon.com obtained from LOBSTAR (Limit Order Book System – The Efficient Reconstructor, https://lobsterdata.com).

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. 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). 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 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.

Recently, the advanced technology and algorithmic trading systems that characterize modern markets allow traders to submit hundreds of orders every second. 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 high-frequency trading arms race). In addition, many limit orders are quickly canceled after their placement as shown by Boehmer et al. (2005).

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 limit order book, 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 vector autoregressive model for quotes and depth. Such mechanical price changes are also illustrated in the stylized limit order book 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.

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 (least-squares estimates of the coefficient of order flow imbalances) are found to be in line with their stylized limit order book 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. 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.

Following Cont et al. (2014), this study examines the price impact of order flow imbalances for Amazon.com on June 21, 2012. In contrast to Cont et al. (2014), the estimation results suggest the nonlinear or concave relation between price changes and order flow imbalances. Nevertheless, the intraday pattern of the estimated price impact is roughly similar to Cont et al. (2014). That is, the price impact is high around the time the market opens but small around its close. On the other hand, the quadratic price impact shows the exact opposite intraday pattern, suggesting that the nonlinear or concave relation between price changes and order flow imbalances is especially evident after the market opens.

The rest of this paper is organized as follows. Section 2 describes the price impact model based on stylized limit order book model introduced by Cont et al. (2014). Section 3 introduces the dataset of Amazon.com as well as the construct variables, and provides their summary statistics. Section 4 presents the estimation results. Finally, Section 5 concludes the paper with discussions on further studies.

2 Price Impact Model

Cont et al. (2014) suggest the stylized limit order book model which allows us to explicitly compute the instantaneous effect of order book events (marketable orders, limit orders, and cancellations). The stylized limit order book model assumes: an order book in which the number of shares (depth) at each price level beyond the best bid and ask is equal to D; order arrivals and cancellations occur only at best bid and ask; and when bid (or ask) size reaches D, the next passive order arrives 1 tick above (or below) the best quote, initializing a new best level.

Let L_k^b and C_k^b be the total size of buy orders that arrived to and canceled from current best bid during a time interval $[t_{k-1}, t_k]$. In addition, let M_k^a be the total size of marketable buy orders that arrived to current best ask, and P_k^b be the best bid price at time t_k. Similarly let L_k^a and C_k^a be the total size of sell orders, M_k^b be the total size of marketable sell orders that arrived to current best bid, and P_k^a be the best ask price.

In this setup, the price changes $\Delta P_k^{a,b} = P_k^{a,b} - P_{k-1}^{a,b}$ and order flows $L_k^{a,b}$, $C_k^{a,b}$, $M_k^{a,b}$ are linearly related as follows:

$$\Delta P_k^a = \delta \left\lceil \frac{L_k^a - C_k^a - M_k^b}{D} \right\rceil, \Delta P_k^b = \delta \left\lceil \frac{L_k^b - C_k^b - M_k^a}{D} \right\rceil,$$

where δ denotes the tick size and $\lceil \cdot \rceil$ represents the ceil function. The price changes are remarkably simple. They do not involve any parameters and the impact of all order book events depends only on their net imbalance.

Figures 1–3 (reprinted from Figures 1–3 in Cont et al. (2014)) illustrate the linear relation with $D=5$. First, Figure 1 shows that marketable sell order of size 15 decreases the price by 3δ. Then, Figure 2 shows that limit buy order of size 7 increases the price by 2δ and the total price change is $-\delta$. Finally,

Figure 3 shows that cancellation of limit buy order of size 4 decreases the price by δ and the total price change is -2δ.

In the stylized order book model, the relation between mid-price changes normalized by tick size $P_k=(P_k^b+P_k^a)/2\delta$ and order flows are summarized as follows:

$$\Delta P_k = \frac{OFI_k}{2D} = \epsilon_k,$$

$$OFI_k = L_k^b - C_k^b - M_k^b - L_k^a - C_k^a - M_k^a, \tag{1}$$

where OFI_k is the order flow imbalance and ϵ is the truncation error due to the ceil function.

Real financial markets and actual order books are, of course, far more complex than the stylized limit order book model. As noted in Cont et al. (2014), order arrivals and cancellations occur at all price levels and the depth distribution is not uniformly distributed. Thus, Cont et al. (2014) assume a noisy relation between price changes and order flow imbalances:

$$\Delta P_{k,i} = \beta_i OFI_{k,i} + \epsilon_{k,i}, \tag{2}$$

where $\Delta P_{k,i}$ and $OFI_{k,i}$ are price changes and order flow imbalances for short intervals of time $[t_{k-1,i}, t_{k,i}] \subset [T_{i-1}, T_i]$, and $[T_{i-1}, T_i]$ are longer intervals. β_i is a price impact coefficient for an i-th time interval and $\epsilon_{k,i}$ is a noise term summarizing various unspecified factors such as orders at deeper levels. For each longer interval $[T_{i-1}, T_i]$, the price impact coefficient β_i are easily estimated by ordinary least squares. Moreover, the well-known intraday seasonality effects can be considered by estimating the model for several intervals during one day.

3 Data

The dataset used in this study is constructed from order book data of Amazon.com on June

Figure 1: Linear relation between price change and marketable sell order and in the stylized limit order book model of Cont et al. (2014)

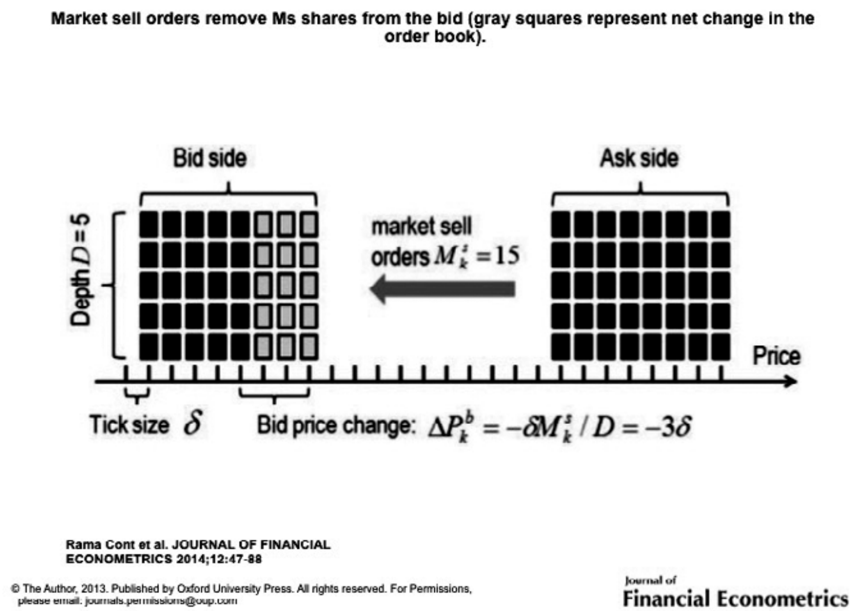


Figure 2: Linear relation between price change and marketable sell and limit buy orders in the stylized limit order book model of Cont et al. (2014)

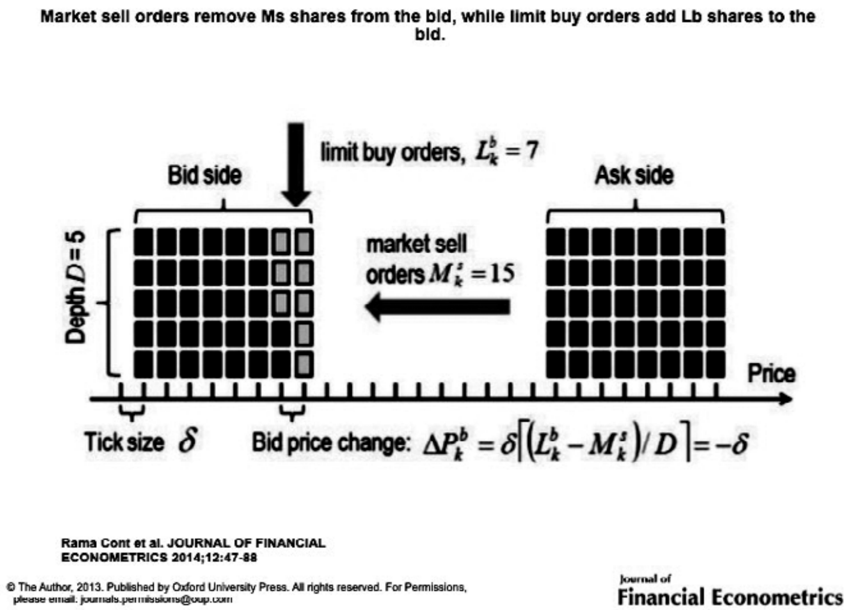
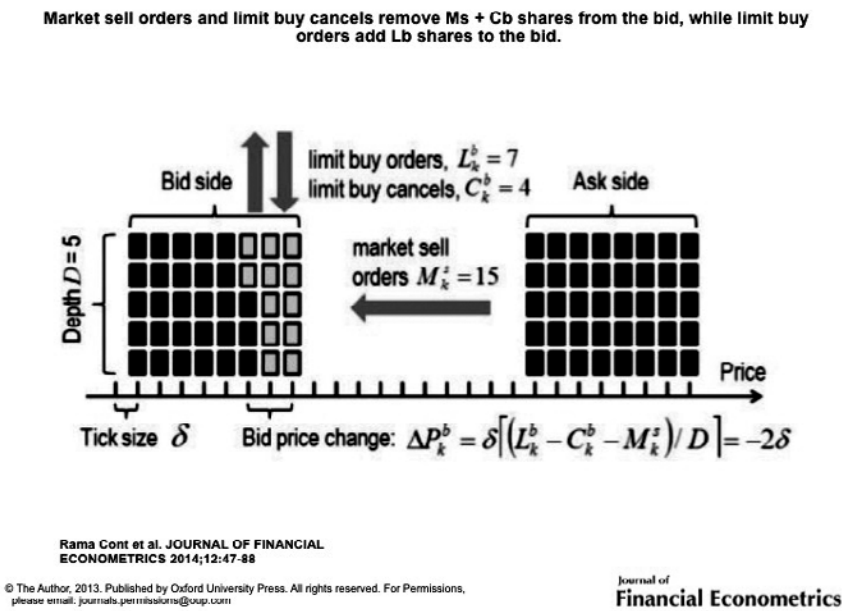


Figure 3: Linear relation between price change and cancellation of limit buy order as wellas marketable sell and limit buy orders in the stylized limit order book model of Cont et al. (2014)



21, 2012. The data contains all events that change the state of limit order book in 9:30–16:00. 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 time, type, order ID, size (number of shares), price (dollar price times 10,000), and direction (-1 for sell limit order and +1 for buy limit order). The types of orders are described in Table 1.

Table 2 presents the summary statistics of size of each order. Limit orders and partial or total deletion of limit orders consist of more than 95% of observations and exhibit extremely large values. They also imply that most limit orders are cancelled or deleted, which is consistent with Boehmer et al. (2005). Further, executions consist of only 4% or so, and exhibit small mean and low standard deviation compared to those of limit orders.

Figure 4 shows the transition of the mid-quote price (average of the best bid and offer prices, divided by 10,000, i.e., converted to dollar price). Reflecting that orders arrive randomly rather than regularly, the horizontal axis, representing time, is not regularly spaced. The length of each 30-minute interval imply that the order submissions are relatively active in 9:30–11:00 and 15:00–15:30, and especially active in 15:30–16:00, which is consistent with the U-shaped market activity pattern observed in a number of studies. Overall, The stock price decreases by 3.18 dollars (1.42%) in 9:30–15:30.

3.1 Variable Construction

Extracting the order book events on the best bid and offer, the sample examined herein contains 55,070 observations. From the best bid and offer data, mid-quote returns, denoted by r_t, are computed over ten-second intervals.

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

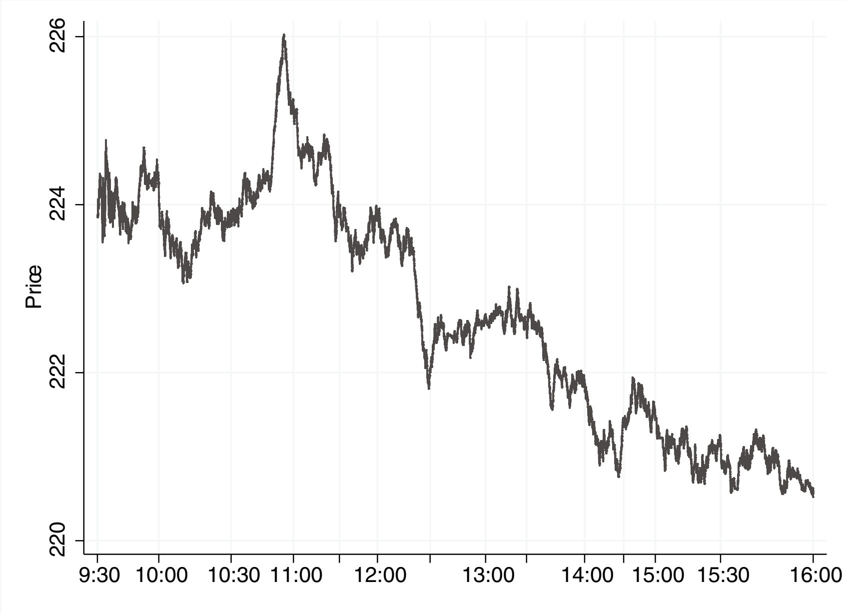
Table 1: Types of Orders

1: Submission of a new limit order
2: Cancellation (Partial deletion of a limit order)
3: Deletion (Total deletion of a limit order)
4: Execution of a visible limit order
5: Execution of a hidden limit order

Table 2: Summary statistics of size of each order for Amazon.com on June 21, 2012, 9:30–16:00. Obs represents the number of observations, RF the relative frequency, and SD the standard deviation.

Type	Obs	RF	Mean	SD	Min	Max
1: Limit order	131,954	48.92%	98.73	172.53	1	33570
2: Cancellation	2,917	1.08%	118.45	46.79	1	300
3: Deletion	123,458	45.77%	96.77	171.61	1	33570
4: Execution (visible)	8,974	3.33%	68.34	95.73	1	4000
5: Excecution (hidden)	2,445	0.91%	80.78	108.03	1	1968

Figure 4: Mid-quote price for Amazon.com on June 21, 2012, 9:30-16:00.



its size. Then, an order book event is defined as

$$e_n = q_n^b I_{\{P_n^b \geq P_{n-1}^b\}} - q_{n-1}^b I_{\{P_n^b \leq P_{n-1}^b\}} - q_n^a I_{\{P_n^a \leq P_{n-1}^a\}} + q_{n-1}^a I_{\{P_n^b \geq P_{n-1}^b\}}, \tag{3}$$

where $I_{\{A\}}$ denotes the indicator function of event A. 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.

Figure 5 shows the transition of order book events. There are extremely large positive events followed by the comparable negative events. Figure 6 shows the order book events without those outliers. Positive and negative events appear to occur one after another, implying that most limit orders are cancelled immediately. These phenomena are consistent with those of Table 2.

Order flow imbalances, denoted by f_t, are computed by aggregating e_n over ten-second intervals. Since e_n represents a change in the order book at the best bid and ask prices, f_t represents the imbalance between supply and demand at the best bid and ask prices.

3.2 Summary Statistics

Table 3 presents the summary statistics of the mid-quote returns r_t in basis points (multiplied by 10,000) and order flow imbalances f_t in thousands (divided by 1,000). Both the variables exhibit excess kurtosis and occasional large values. In addition, f_t is right skewed. Figures 7 and 8 show the changes of these variables, confirming the occasional large values especially for f_t. Further, histograms in Figures 9 and 10 confirm the excess kurtosis and non-normality of the variables.

4 Estimation Results

Let $r_{k,i}$ and $f_{k,i}$ be the mid-quote returns and order flow imbalances over the k-th 10-second interval in the i-th 30-minute interval. Then,

Figure 5: Order book events for Amazon.com on June 21, 2012, 9:30–16:00.

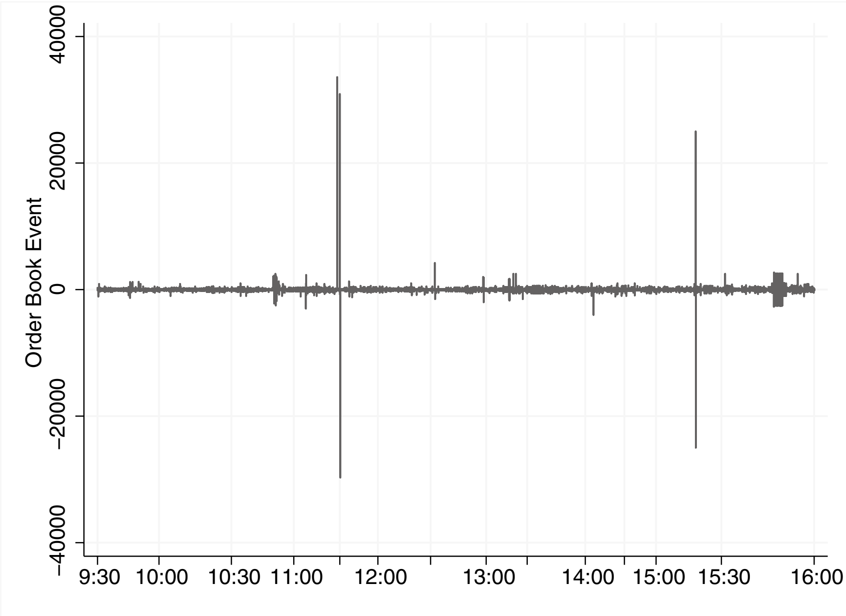


Figure 6: Order book events without outliers for Amazon.com on June 21, 2012, 9:30– 16:00.

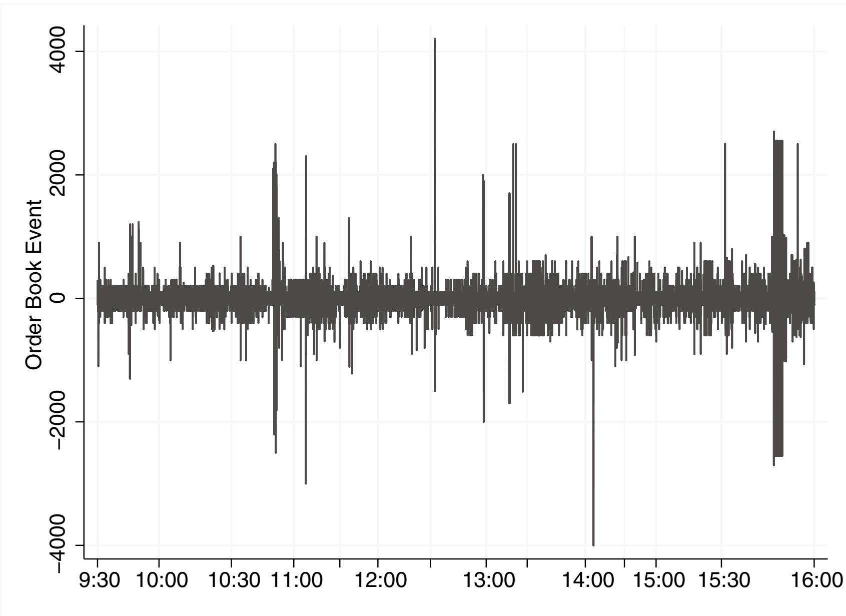


Table 3: Summary statistics of mid-quote returns r_t in basis points (multiplied by 10,000) and order flow imbalances f_t in thousands (divided by 1,000) for Amazon.com on June 21, 2012, 9:30-16:00. Obs represents the number of observations and SD the standard deviation.

	Obs	Mean	Median	SD	Skew	Kurt	Min	Max
r_t	2,260	−0.060	0.000	2.997	0.034	8.713	−20.980	18.769
f_t	2,260	−0.028	−0.003	1.473	6.462	253.398	−26.423	34.876

Figure 7: Mid-quote return in basis points (multiplied by 10,000) over ten-second interval for Amazon.com on June 21, 2012, 9:30-16:00.

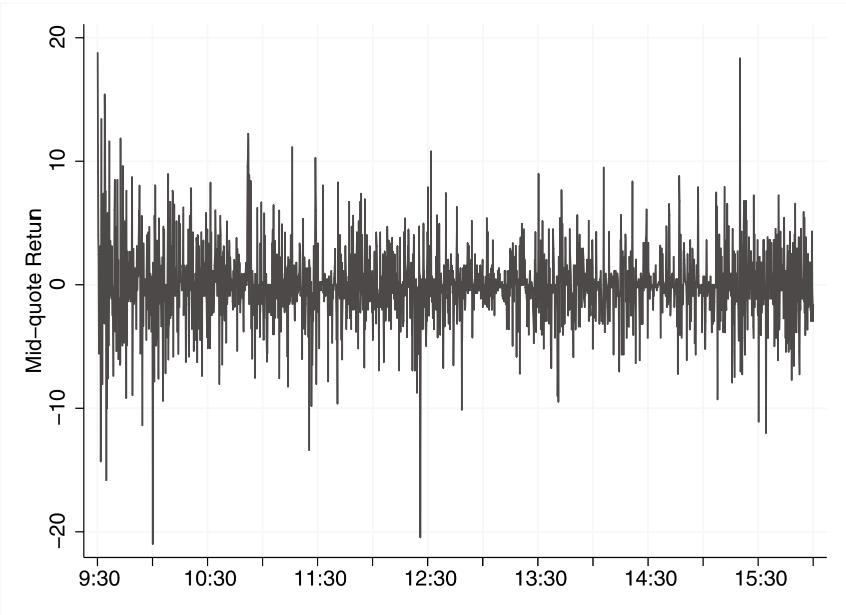
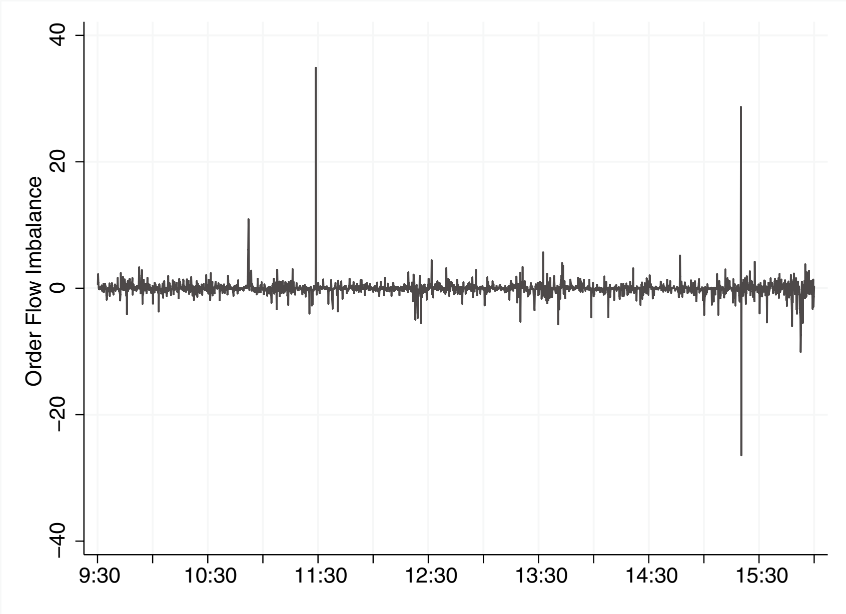


Figure 8: Order flow imbalance in thousands (divided by 1,000) over ten-second interval for Amazon.com on June 21, 2012, 9:30–16:00.



the price impact model with constant term,

$$r_{k,i}=\alpha_i+\beta_i f_{k,i}+\epsilon_{k,i}, \tag{4}$$

is estimated by the least-squares method. Table 4 presents the estimation results. The price impact coefficients β_i for 30-minute intervals $i=1, 2, ..., 13$ are all significantly positive and all the constant terms α_i are insignificant except for 15:00–15:30. In addition, the coefficient of determination R^2 ranges between 37.6% and 63.6%. These results are consistent with Cont et al. (2014).

To check for higher order or nonlinear dependence, an augmented price impact model,

$$r_{k,i}=\alpha_i^Q+\beta_i^Q+f_{k,i}+\gamma_i^Q f_{k,i}|f_{k,i}|+\epsilon_{k,i}^Q, \tag{5}$$

is estimated. Table 5 presents the estimation results. Again, the price impact coefficients β_i^Q are all significantly positive and only a few of constant terms α_i are significant. Many of the quadratic impact coefficients γ_i^Q are significantly negative. Moreover, the magnitude of the price impact coefficient β_i^Q is higher than that of β_i. In contrast to Cont et al. (2014), theses results suggest a nonlinear relation between price changes and order flow imbalances, which is consistent with the concave price impact function observed in Lillo et al. (2003).

Figures 11 and 12 show the estimated price impact coefficients β_i^Q and quadratic impact coefficients γ_i^Q for the augmented price impact model (5), respectively. The price impact is high around the time the market opens but small around its close, which is similar to Cont et al. (2014) except the jumps in 11:30–12:00 and 14:00–14:30. On the other hand, the quadratic impact is small around its open and high around its close with drops in 11:30–12:00 and 14:00–14:30, which is exact opposite to the price impact. This suggests that the nonlinear or concave relation between price changes and order flow imbalances is especially evident after

Figure 9: Histogram of mid-quote returns in basis points (multiplied by 10,000) over ten-second interval for Amazon.com on June 21, 2012, 9:30-16:00. The line represents the normal density curve.

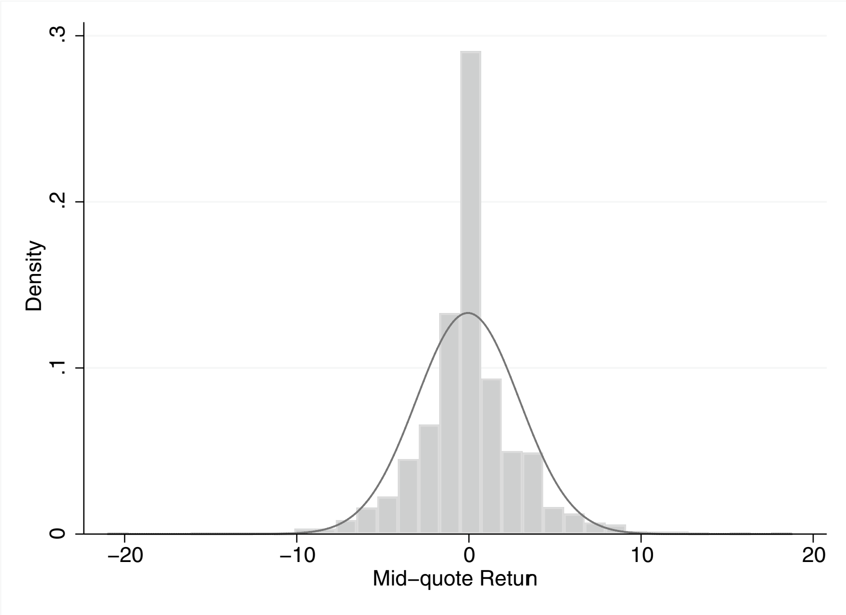


Figure 10: Histogram of order flow imbalances in thousands (divided by 1,000) over ten-second interval for Amazon.com on June 21, 2012, 9:30-16:00. The line represents the normal density curve.

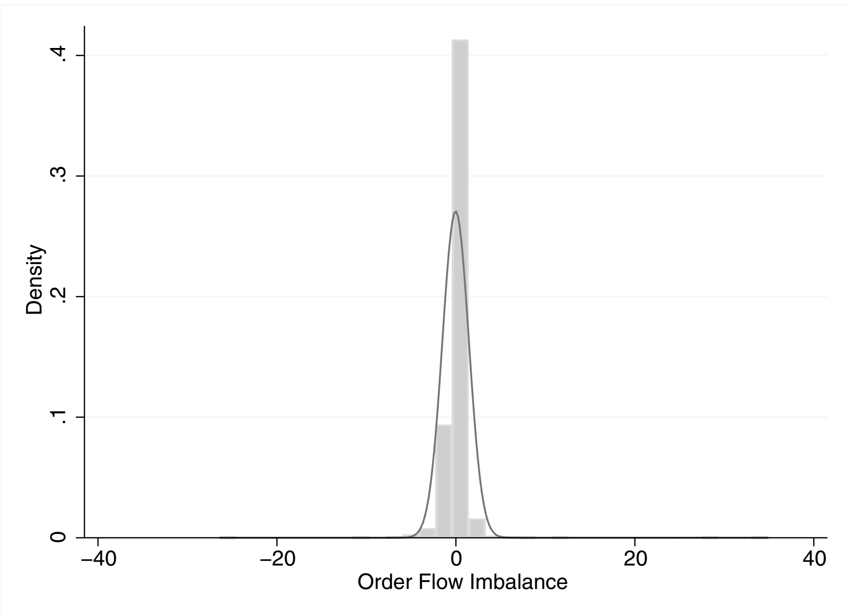


Table 4: Estimation results of the price impact model $r_{k,i}=\alpha_i+\beta_i f_{k,i}+\epsilon_{k,i}$ for each 30-minute interval i =1, 2, . . . , 13 on June 21, 2012, 9:30-16:00. Obs represents the number of observations and R^2 the coefficient of determination. Robust standard errors are presented in parentheses.

Interval	Obs	$\hat{\alpha}_i$		$\hat{\beta}_i$		R^2
09:30-10:00	178	−0.151	(0.285)	3.497	(0.486)	0.376
10:00-10:30	177	−0.062	(0.164)	4.120	(0.485)	0.651
10:30-11:00	173	0.008	(0.156)	1.811	(0.314)	0.534
11:00-11:30	176	−0.056	(0.135)	2.829	(0.338)	0.621
11:30-12:00	177	0.025	(0.117)	3.314	(0.423)	0.625
12:00-12:30	176	−0.167	(0.124)	2.508	(0.356)	0.638
12:30-13:00	173	−0.107	(0.107)	2.591	(0.301)	0.619
13:00-13:30	167	0.027	(0.091)	1.753	(0.164)	0.598
13:30-14:00	170	−0.132	(0.139)	1.707	(0.193)	0.542
14:00-14:30	170	0.192	(0.108)	2.425	(0.395)	0.604
14:30-15:00	167	0.061	(0.111)	2.238	(0.299)	0.571
15:00-15:30	173	0.267	(0.122)	2.149	(0.241)	0.636
15:30-16:00	180	0.196	(0.147)	1.162	(0.226)	0.436

Table 5: Estimation results of the augmented price impact model $r_{k,i}=\alpha_i^Q+\beta_i^Q f_{k,i}+\gamma_i^Q f_{k,i}|f_{k,i}|+\epsilon_{k,i}$ for each 30-minute interval i = 1, 2, . . . , 13 on June 21, 2012, 9:30- 16:00. Obs represents the number of observations and $\overline{R}^2$ the adjusted coefficient of determination. Robust standard errors are presented in parentheses.

Interval	Obs	$\hat{\alpha}_i^Q$		$\hat{\beta}_i^Q$		$\hat{\gamma}_i^Q$		$\overline{R}^2$
09:30-10:00	178	−0.213	(0.260)	6.299	(0.772)	−1.341	(0.245)	0.441
10:00-10:30	177	−0.087	(0.158)	5.238	(0.495)	−0.634	(0.378)	0.663
10:30-11:00	173	0.032	(0.144)	3.315	(0.300)	−0.210	(0.032)	0.636
11:00-11:30	176	−0.043	(0.131)	3.922	(0.528)	−0.492	(0.312)	0.643
11:30-12:00	177	−0.066	(0.103)	5.099	(0.559)	−0.853	(0.238)	0.680
12:00-12:30	176	−0.182	(0.120)	3.103	(0.494)	−0.171	(0.214)	0.643
12:30-13:00	173	−0.108	(0.107)	3.169	(0.380)	−0.253	(0.144)	0.627
13:00-13:30	167	0.000	(0.087)	2.484	(0.245)	−0.256	(0.068)	0.629
13:30-14:00	170	−0.125	(0.133)	2.589	(0.281)	−0.261	(0.077)	0.580
14:00-14:30	170	0.228	(0.106)	3.892	(0.327)	−0.651	(0.095)	0.689
14:30-15:00	167	0.104	(0.104)	3.074	(0.397)	−0.329	(0.101)	0.605
15:00-15:30	173	0.333	(0.118)	3.489	(0.391)	−0.538	(0.196)	0.693
15:30-16:00	180	0.114	(0.135)	2.246	(0.225)	−0.213	(0.037)	0.571

Figure 11: Estimated price impact coefficients β_i^Q for each 30-minute interval i = 1, 2, . . . , 13 on June 21, 2012, 9:30–16:00.

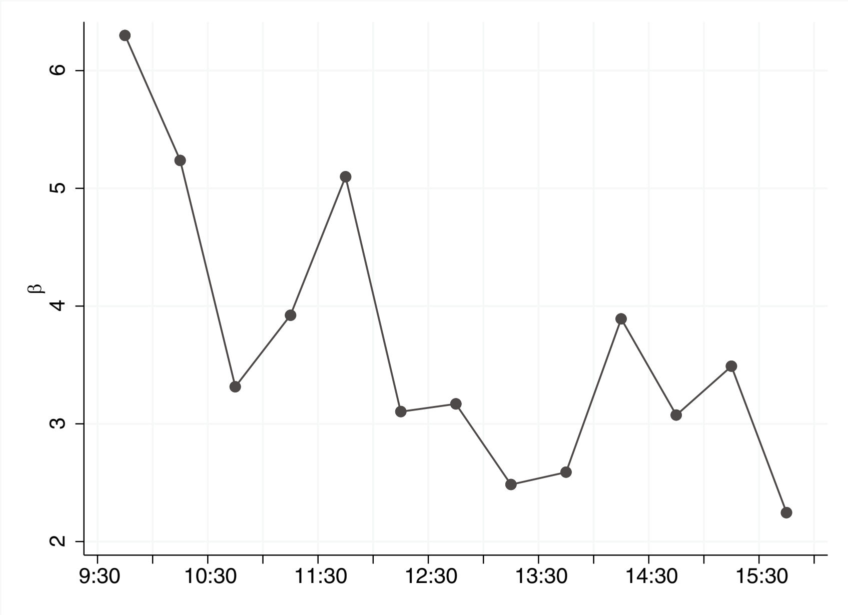
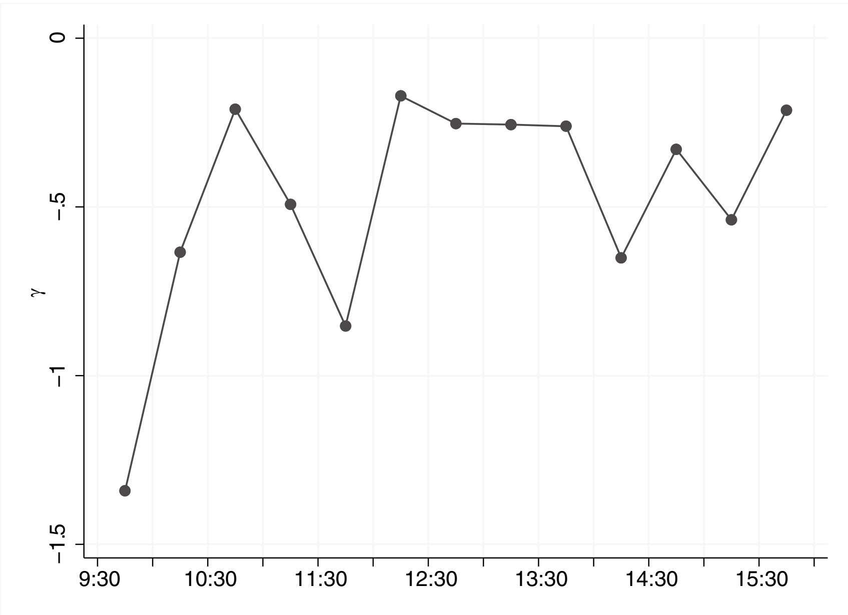


Figure 12: Estimated quadratic impact coefficients γ_i^Q for each 30-minute interval i=1, 2, . . . , 13 on June 21, 2012, 9:30–16:00.



the market opens.

5 Conclusion

This study investigates the price impact of order flow imbalances constructed from the order book data of Amazon.com on June 21, 2012. In contrast to Cont et al. (2014), the estimation results suggest the nonlinear or concave relation between price changes and order flow imbalances. Nevertheless, the intraday pattern of the estimated price impact is roughly similar to Cont et al. (2014). That is, the price impact is high around the time the market opens but small around its close. On the other hand, the quadratic price impact shows the exact opposite intraday pattern, suggesting that the nonlinear or concave relation between price changes and order flow imbalances is especially evident after the market opens.

The (augmented) limit order book model employed in this study can be extended by specifying different order book events (marketable orders, limit orders, and cancellations) 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 for multiple assets. 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. Such issues remain objects of further study.

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