Dynamic Causality between Intraday Return and Order Imbalance in NASDAQ Speculative New Lows

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ABSTRACT

Most studies explore the relation between return and order imbalance on some extraordinary events. We examine intraday behaviors when the speculative stocks reach 52-week new low records by a multiple hypotheses testing method. The size-stratified results show that when the firm size is smaller, the percentage of firms exhibiting a unidirectional relationship from order imbalances to returns is larger, implying that order imbalance could be a better indicator for predicting returns in small firm size quartile. The order imbalance-based trading strategies are powerful in the afternoon for the percentage of firms exhibiting a unidirectional relationship from order imbalance to return is the greatest in this period.

INTRODUCTION

A lot of literatures investigate the relation between trading volume and return dynamics. Although volume is an important linkage between stock return and trading activity (a summarized review by Karpoff, 1987), volume alone conceals some important information about trading (Chan & Fong, 2000). For example, given a reported volume of 100,000 shares, there are many possibilities. It might be 50,000 seller-initiated shares and 50,000 buyer-initiated shares. In an extreme case, it might be 100,000 seller-initiated shares or 100,000 buyer-initiated shares. As a result, the order imbalances convey more information than volume itself does. A large order imbalance has a great impact on price movement (Marsh & Rock, 1986; Lee, 1992; Madhavan & Smidt, 1993; Stoll 2000; Chordia & Subrahmanyam, 2002), for it could signal private information (Kyle, 1985) and for it would exert pressure on market maker’s inventory, thereby prompting a change in quotes (Stoll, 1978; Ho & Stoll, 1983; Spiegel & Subrahmanyam, 1995).

Although the literature suggests a strong association between stock returns and order imbalances, a discussion of the causal relationship between them is rare. Brown, Walsh and Yuen (1997) find bi-directional causality between returns and order imbalances, but not beyond a single day. They also find that the number of orders can explain current return, but the dollar value of orders can explain both current and future returns. Huang and Stoll(1994) find intraday return could be predicted by order imbalance. Moreover, Chordia and Subrahmanyam (2004) find that imbalance-based trading strategies yield statistically significant returns.

To know whether information asymmetry has a significant influence on return-order imbalance relation, we need a measure of information asymmetry. Since information asymmetry is not directly observable, a suitable proxy is necessary. Lo and MacKinlay (1990) and Llorente, Michaely, Sarr, and Wang (2002) use firm size to measure information asymmetry. They argue that firms with larger size have a lower degree of information asymmetry. The larger firm sizes, the more regulations, debt holders, equity holders and analysts are involved in. Therefore, the extent of transparency in larger firm size is higher than that in smaller firms. Easley, Kiefer, O’Hara and Paperman (1996) show that private information is more important

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1 The market makers would revise the price downward (upward) when there are excess sell (buy) orders.
for infrequent stocks. Although information events take place more rarely in these stocks, it has a greater impact on trading when new information occurs. Besides, they present that low volume stocks have a higher probability of informed trading.

Most studies explore the relation between return and order imbalance on some extraordinary events. For example, Blume, MacKinlay and Terker (1989) and Lauterbach and Ben-Zion (1993) examine order imbalances around the October 1987 crash, while Lee (1992) analyzes order imbalances around earnings announcements. The above events provide an ideal laboratory in which to examine the adjustment of prices of individual stocks to major changes of order imbalances. Llorente, et al. (2002) recognize that there are two types of trades, which are hedging and speculative trades. They find that the relative higher importance of speculative trade is associated with higher information asymmetry. Therefore, we examine the relation between return and order imbalance in the speculative stocks listed on NASDAQ with top 10 declining ratio.

Unlike traditional pairwise hypothesis testing, we adopt a systematic multiple-hypothesis testing method to determine a specific causal relation between returns and order imbalances to avoid the potential bias induced by restricting the causal relationship to a single alternative hypothesis. Besides, we use the firm size and trading volume as proxies of information asymmetry to see the impact of these proxies on the causal relationship between returns and order imbalances. In addition, Cornell and Sirri (1992) find insider trading often take place from noon to 2 P.M. in a specific illegal insider trading, while we use regression analysis to infer when the insider trading often take place during the day.

According to multiple hypotheses testing method, we find that the smaller firm size is associated with the larger percentage of firms exhibiting a unidirectional relationship from order imbalances to returns, implying that order imbalance could be a better indicator for predicting returns in small firm size quartile. Moreover, the order imbalance-based trading strategies are more powerful from 11:30 A.M. to 2 P.M. than others for the percentage of firms exhibiting a unidirectional relationship from order imbalance to return is the greatest in this period.

The rest of this paper is organized as follows. Section 2 describes data and methodology. In section 3, we discuss empirical results. Section 4 concludes.

DATA AND METHODOLOGY

Data

1. Data Sample and Sources

Owing to the high speeds of adjustment in financial markets, studies based upon daily data would fail to catch information contained in intraday market movements. Thus, we use the 90-second cumulative transaction data, including order time, order imbalances (excess buy orders) and prices, and select the NASDAQ speculative stocks which reach 52-week new low records as our samples. For each stock, we define the order imbalance as the share of buyer-initiated trades minus that of seller-initiated trades. Our sample period is from Oct. 2004 to Mar. 2005. These data are available on the Island-ECN website, which

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2. Lee, Fok and Liu (2001) use 6-minute intervals with each interval containing nearly 12 trades on average. Ekinci (2004) constructs 5-min intervals for an intraday analysis of stocks with 27.3 trades per interval on average. For our sample period is only one day, we shorten the time interval. In addition, for NASDAQ dealers are required to report trades within 90 seconds, we use 90-second intervals to catch the intraday seasonality.

3. According to Ronald, Christine and Uday (2005), transaction price is better than midpoint of bid-ask spread as a proxy of asset value.

4. The Island-ECN website is “http://www.island.com”. We would sign trades using Lee and Ready (1991) algorithm if we use the NYSE Trades and Automated Quotations (TAQ) databases. Unlike TAQ databases, the “Time and Sales” database provided by Island-ECN has indicated the sign of trades.
offers U.S. broker-dealers access to one of the most robust liquidity pools in NASDAQ equities.

Due to the following main advantages, there are more investors trading on ECN (Electronic Communication Network). Investors can reduce market interposition cost and prevent from middlemen’s prying eyes. In addition, Barclay, Hendershott and McCormick (2003) find ECN offers the advantages of anonymity and speed of execution, which attract informed traders. There is more private information revealed through ECN trades than though market maker trades. As a result, we choose an information transparently provided ECN—Island, as our data source.

2. Descriptive Statistics

Panel A of Table 1 presents the descriptive statistics of buyer (seller)-initiated trades and order imbalances during the day when 73 speculative stocks reach 52-week new low records from Oct. 2004 to Mar. 2005. We find that the mean of order imbalance is 0.04 percent of total shares, indicating that the means of order imbalance are almost equal to zero, indicating that investors’ intention to buy stocks is virtually the same as that to sell stocks during the day when the speculative stocks reach 52-week new low records.

The means and standard deviations of buy and sell orders per trade are presented in Panel B of Table 1. The mean of order imbalance per buy trade is 199.77 and that of sell orders per trade is -209.90, indicating that the shares is higher when investors sell stocks than those when they buy stocks.

Methodology

According to Chen and Wu (1999), we define four relationship between two random variables, \( x_1 \) and \( x_2 \), in terms of constraints on the conditional variances of \( x_{1(T+1)} \) and \( x_{2(T+1)} \) based on various available information sets, where \( x_i = (x_{i1}, x_{i2}, ..., x_{it}), i = 1, 2 \), are vectors of observations up to time period \( T \).

**Table 1.** Descriptive statistics of buy/sell trades and order imbalances.

<table>
<thead>
<tr>
<th></th>
<th>Maximum</th>
<th>Minimum</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of buy shares</td>
<td>392605</td>
<td>11801</td>
<td>133870</td>
</tr>
<tr>
<td>Number of sell shares</td>
<td>480560</td>
<td>8900</td>
<td>121973</td>
</tr>
<tr>
<td>Order imbalance/Total trades(%)</td>
<td>-0.10</td>
<td>0.14</td>
<td>0.04</td>
</tr>
</tbody>
</table>

**Panel B** Means and standard deviations of order per trade

<table>
<thead>
<tr>
<th></th>
<th>Maximum</th>
<th>Minimum</th>
<th>Mean</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Order imbalance per buy trade</td>
<td>8300.00</td>
<td>1.00</td>
<td>199.77</td>
<td>203.05</td>
</tr>
<tr>
<td>Order imbalance per sell trade</td>
<td>-44100.00</td>
<td>-1.00</td>
<td>-209.90</td>
<td>348.56</td>
</tr>
</tbody>
</table>

**Definition 1: Independency,** \( x_1 \wedge x_2 \):

\[
Var(x_{1(T+1)} | x_1) = Var(x_{3(T+1)} | x_1, x_2) = Var(x_{1(T+1)} | x_1, x_2, x_{2(T+1)})
\]

(1)

and

\[
Var(x_{2(T+1)} | x_2) = Var(x_{2(T+1)} | x_1, x_2) = Var(x_{3(T+1)} | x_1, x_2, x_{3(T+1)})
\]

(2)

**Definition 2: Contemporaneous relationship,** \( x_1 \prec \succ x_2 \):

\( x_1 \) and \( x_2 \) are contemporaneously related if
\[
\text{Var}(x_1|_{T+1})|_x = \text{Var}(x_1|_{T+1})|_{x_1, x_2} \quad \text{and} \quad \text{Var}(x_2|_{T+1})|_x = \text{Var}(x_2|_{T+1})|_{x_1, x_2} 
\]

(3)

and

\[
\text{Var}(x_1|_{T+1})|_{x_1} = \text{Var}(x_1|_{T+1})|_{x_1, x_2} \quad \text{and} \quad \text{Var}(x_2|_{T+1})|_{x_2} > \text{Var}(x_2|_{T+1})|_{x_1, x_2} 
\]

(4)

**Definition 3: Unidirectional relationship,** \(x_j = > x_2\):

There is a unidirectional relationship from \(x_j\) to \(x_2\) if

\[
\text{Var}(x_1|_{T+1})|_{x_1} = \text{Var}(x_1|_{T+1})|_{x_1, x_2} \quad \text{and} \quad \text{Var}(x_2|_{T+1})|_{x_2} > \text{Var}(x_2|_{T+1})|_{x_1, x_2} 
\]

(5)

**Definition 4: Feedback relationship,** \(x_j < = > x_2\):

There is a feedback relationship between \(x_j\) and \(x_2\) if

\[
\text{Var}(x_1|_{T+1})|_{x_1} > \text{Var}(x_1|_{T+1})|_{x_1, x_2} \quad \text{and} \quad \text{Var}(x_2|_{T+1})|_{x_2} > \text{Var}(x_2|_{T+1})|_{x_1, x_2} 
\]

(6)

To explore the dynamic relationship of a bivariate system, we form the five statistical hypotheses in the Figure 1, where the necessary and sufficient conditions corresponding to each hypothesis are given in terms of constraints on the parameter values of the VAR model.

To determine a specific causal relationship, we use a systematic multiple hypotheses testing method. Unlike the traditional pairwise hypothesis testing, this testing method avoids the potential bias induced by restricting the causal relationship to a single alternative hypothesis. To implement this method, we employ results of several pairwise hypothesis tests. For instance, in order to conclude that \(x_j = > x_2\), we need to establish that \(x_j < = > x_2\) and to reject that \(x_j = > x_2\). To conclude that \(x_j < = > x_2\), we need to establish that \(x_j < = > x_2\) as well as \(x_j = > x_2\) and also to reject \(x_j\) \& \(x_2\). In other words, it is necessary to examine all five hypotheses in a systematic way before we draw a conclusion of dynamic relationship. The following presents an inference procedure that starts from a pair of the most general alternative hypotheses.

**Figure 1. Hypotheses on the dynamic relationship of a bivariate system**

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>The VAR test</th>
</tr>
</thead>
<tbody>
<tr>
<td>(H_1: x_1 \land x_2)</td>
<td>(\varphi_{12} (L) = \varphi_{21} (L) = 0) and (\sigma_{12} = \sigma_{21} = 0)</td>
</tr>
<tr>
<td>(H_2: x_1 &lt; = &gt; x_2)</td>
<td>(\varphi_{12} (L) = \varphi_{21} (L) = 0)</td>
</tr>
<tr>
<td>(H_3: x_1 = &gt; x_2)</td>
<td>(\varphi_{21} (L) = 0)</td>
</tr>
<tr>
<td>(H_4: x_1 = &gt; x_2)</td>
<td>(\varphi_{12} (L) = 0)</td>
</tr>
</tbody>
</table>

Our inference procedure for exploring dynamic relationship is based on the principle that a hypothesis should not be rejected unless there is sufficient evidence against it. In the causality literature, most tests intend to discriminate between independency and an alternative hypothesis. The primary purpose of the literature cited above is to reject the independency hypothesis. On the contrary, we intend to identify the nature of the relationship between two financial series. The procedure consists of four testing sequences, which implement a total of six tests (denoted as (a) to (f)), where each test examines a pair of hypotheses. The four testing sequences and six tests are summarized in a decision-tree flow chart in Figure 2.
EMPIRICAL RESULTS

To explore the dynamic relationship between two variables, we impose the constraints in the upper panel of Figure 1 on the VAR model. In Table 2, we present the results of tests of hypotheses on the dynamic relationship in Figure 1. We show that a unidirectional relationship from returns to order imbalances is 19.18% of the sample firms for the entire sample, while a unidirectional relationship from order imbalances to returns is 9.59%. The percentage of firms that fall into the independent category is relatively small (6.85%). Moreover, 63.01% of firms exhibit a contemporaneous relationship between returns and order imbalances. Finally, 1.37% of firms show a feedback relationship between returns and order imbalances. The percentage of firms reflecting a unidirectional relationship from returns to order imbalances is about twice as large as that from order imbalances to returns, suggesting that order imbalance is not always a good indicator for predicting future returns, although many articles document that future daily returns could be predicted by daily order imbalances (Brown, et al. 1997; Chordia and Subrahmanyam, 2004). This can be explained as follows. During the trading day when the stocks reach 52-week new low records, investors always place their sell orders after the stock prices continuously fall. Therefore, the percentage of firms reflecting a unidirectional relationship from returns to order imbalances is higher than that from order imbalances to returns, implying that the order imbalance-based trading strategies are not powerful during the trading day when the stocks reach 52-week new low records. In addition, the percentage of firms exhibiting a contemporaneous relationship is almost over sixty percent than that reflecting a feedback relationship, indicating that the interaction between returns and order

Figure 2. Test flow chart of a multiple hypothesis testing procedure

Test Sequence I
(a) $H_1$ vs. $H_4$
(b) $H_3^*$ vs. $H_4$

$E_4$: (a) not reject $H_3$
(b) not reject $H_3^*$

Test Sequence II
(c) $H_2$ vs. $H_1$
(d) $H_2$ vs. $H_3^*$

$E_7$: (c) reject $H_2$
(d) reject $H_2$

Test Sequence III
(e) $H_2$ vs. $H_4$

$E_9$: (e) reject $H_2$

$E_1$: (a) reject $H_1$, (b) reject $H_1^*$
$E_2$: (a) reject $H_1$, (b) not reject $H_1^*$
$E_3$: (a) not reject $H_3$, (b) reject $H_3^*$

$E_5$: (c) reject $H_2$, (b) not reject $H_2$
$E_6$: (c) not reject $H_2$, (b) reject $H_2$

$E_8$: (c) not reject $H_2$, (b) not reject $H_2$

$E_{10}$: (e) not reject $H_2$

Test Sequence IV
(f) $H_1$ vs. $H_2$

$E_{11}$: (f) reject $H_1$
$E_{12}$: (f) not reject $H_1$
Table 2. Proportion of detected dynamic relationship between returns and order imbalances (%)

This table reports the results for tests of the hypotheses on dynamic relationship between returns and order imbalances. The percentage of firms explained by each dynamic relationship is based on a 5% significance level of tests.

\[
x_1 \land x_2 \quad x_1 \leftarrow \rightarrow x_2 \quad x_1 \Rightarrow x_2 \quad x_1 \leftarrow x_2 \quad x_1 \leftrightarrow x_2 \quad x_1 \leftrightarrow x_2
\]

Return (\(x_1\)) and order imbalance (\(x_2\))

\[
\begin{array}{cccccc}
6.85 & 63.01 & 19.18 & 9.59 & 1.37 \\
\end{array}
\]

imbalances on the current period is much stronger than that over the whole period.

We use the firm size, average daily trading volume of past three months as proxies of information asymmetry to express how the information asymmetry influences the causal relationship between returns and order imbalances. Table 3 reports the average firm size, average daily trading volume of past three months exhibiting each dynamic relationship between returns and order imbalances. Moreover, in order to provide indirect evidence showing the impact of firm size on the relation between returns and order imbalances. The results in Table 4 indicate that the unidirectional relationship from order imbalances to returns is 8.33% in the small firm size quartile, while the corresponding number is still 8.33% in the large firm size quartile during the entire sample period, which do not show the apparent pattern. Nonetheless, Table 3 shows that the average capitalization of firms exhibiting a unidirectional relationship from order imbalances to returns is smaller than that from returns to order imbalances. This can be explained as follows. When the firm size is smaller, the percentage of firms exhibiting a unidirectional relationship from order imbalances to returns is larger and that from returns to order imbalances is smaller, indicating that order imbalance could be a better indicator for predicting returns in small firm size quartile. Besides, the average capitalization of firms reflecting a

Table 3. Average firm size, average daily trading volume of past three months and the ratio of volume of firm size under each relationship between returns and order imbalances

The units of firm size, trading volume are billion dollars, thousand shares and thousand shares by billion dollars. The percentage of firms explained by each dynamic relationship is based on a 5% significance level of tests.

\[
x_1 \land x_2 \quad x_1 \leftarrow \rightarrow x_2 \quad x_1 \Rightarrow x_2 \quad x_1 \leftarrow x_2 \quad x_1 \leftrightarrow x_2 \quad x_1 \leftrightarrow x_2
\]

Average Capitalization

\[
\begin{array}{cccccc}
0.04 & 0.58 & 0.51 & 0.44 & 0.06 \\
\end{array}
\]

Average trading volume

\[
\begin{array}{cccccc}
1771 & 1844 & 2029 & 2078 & 3679 \\
\end{array}
\]

Table 4. Firm size and proportion of detected dynamic relationship between returns and order imbalances (%)

We divide firms into three groups according to firm size, and then test the multiple hypothesis of the relation between returns and order imbalances. The percentage of firms explained by each dynamic relationship is based on a 5% significance level of tests.

\[
x_1 \land x_2 \quad x_1 \leftarrow \rightarrow x_2 \quad x_1 \Rightarrow x_2 \quad x_1 \leftarrow x_2 \quad x_1 \leftrightarrow x_2 \quad x_1 \leftrightarrow x_2
\]

Small size

\[
\begin{array}{cccccc}
20.83 & 58.33 & 8.33 & 8.33 & 4.16 \\
\end{array}
\]

Medium size

\[
\begin{array}{cccccc}
0.00 & 64.00 & 24.00 & 12.00 & 0.00 \\
\end{array}
\]

Large size

\[
\begin{array}{cccccc}
0.00 & 66.67 & 25.00 & 8.33 & 0.00 \\
\end{array}
\]
contemporaneous relationship is 0.58 billion, which is the greatest among five causal relationship, implying that larger firm size is associated with higher transparency.

Table 5 presents that the percentage of firms exhibiting a unidirectional relationship from order imbalances to returns in small trading volume quartile is 4.16%, while that in large trading volume quartile is 12.50%. Table 3 also shows that the average trading volume of firms exhibiting a unidirectional relationship from order imbalances to returns is larger than that from returns to order imbalances. It indicates that order imbalance could not be a better indicator for predicting returns in small trading volume quartile.

Table 5. Average daily trading volume of past three months and the proportion of detected dynamic relationship between returns and order imbalances (%)

We divide firms into three groups according to average daily trading volume of past three months, and then test the multiple hypothesis of the relation between returns and order imbalances. The percentage of firms explained by each dynamic relationship is based on a 5% significance level of tests.

<table>
<thead>
<tr>
<th></th>
<th>$x_1 \wedge x_2$</th>
<th>$x_1 &lt; x_2$</th>
<th>$x_1 \Rightarrow x_2$</th>
<th>$x_1 \Leftarrow x_2$</th>
<th>$x_1 \Leftarrow x_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small volume</td>
<td>4.16</td>
<td>75.00</td>
<td>16.66</td>
<td>4.16</td>
<td>0.00</td>
</tr>
<tr>
<td>Medium volume</td>
<td>12.00</td>
<td>56.00</td>
<td>20.00</td>
<td>12.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Large volume</td>
<td>4.16</td>
<td>58.33</td>
<td>20.83</td>
<td>12.50</td>
<td>4.16</td>
</tr>
</tbody>
</table>

Table 6 presents that the proportion of the relationship between returns and order imbalances during the time of the day. The percentage of firms exhibiting a unidirectional relationship from order imbalances to returns is 0.00, 10.00 and 20.00 in the period 1, 2 and 3, respectively. It implies that order imbalance-based trading strategies are more powerful in the afternoon than others during the day when the speculative stocks reach 52-week new low records.

Table 6. Proportion of detected dynamic relationship between returns and order imbalances during the time of the day (%)

This table reports the results for tests of the hypotheses on dynamic relationship between returns and order imbalances during the time of the day. The percentage of firms explained by each dynamic relationship is based on a 5% significance level of tests.

<table>
<thead>
<tr>
<th></th>
<th>$x_1 \wedge x_2$</th>
<th>$x_1 &lt; x_2$</th>
<th>$x_1 \Rightarrow x_2$</th>
<th>$x_1 \Leftarrow x_2$</th>
<th>$x_1 \Leftarrow x_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time of day</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period 1</td>
<td>10.00</td>
<td>80.00</td>
<td>10.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Period 2</td>
<td>10.00</td>
<td>60.00</td>
<td>10.00</td>
<td>10.00</td>
<td>10.00</td>
</tr>
<tr>
<td>Period 3</td>
<td>0.00</td>
<td>70.00</td>
<td>10.00</td>
<td>20.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

CONCLUSION

Most studies explore the relation between return and order imbalance on some extraordinary events. Blume et al. (1989) and Lauterbach and Ben-Zion (1993) examine order imbalances around the October 1987 crash, while Lee (1992) analyzes order imbalances around earnings announcements. The above events provide an ideal laboratory in which to examine the adjustment of prices of individual stocks to major changes of order imbalances. Therefore, we examine the relation between return and order imbalance during the day when the speculative stocks reach 52-week new low records.

In this study, we discuss a multiple hypotheses testing method for identifying the dynamic relationship
between returns and order imbalances. The conclusion is as followings. The size-stratified results shows that when the firm size is smaller, the percentage of firms exhibiting a unidirectional relationship from order imbalances to returns is larger and that from returns to order imbalances is smaller, implying that order imbalance could be a better indicator for predicting returns in small firm size quartile. Moreover, the volume-stratified results indicate that order imbalance could not be a better indicator for predicting returns in small trading volume quartile. The order imbalance-based trading strategies are more powerful in the afternoon than others during the day when the speculative stocks reach 52-week new low records.
REFERENCES


