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An analysis of intraday return – order imbalance relation to stealth trading

Abstract

This study employs a time varying GARCH (1,1) model and an ordinary least square (OLS) model to examine the intraday dynamic return-order imbalance relation to stealth trading in the NASDAQ-100 component stocks. The contemporaneous order imbalance-return relation is positively significant. Furthermore, the effect in the medium size is more significant than that in other size categories, which is consistent with stealth trading hypothesis proposed by Barclay and Warner (1993). The impact of order imbalance on return is stronger than that of trading volume, implying that order imbalance convey more information than trading volume does. The contemporaneous order imbalance-return effect is the greatest in the sub-period 2. It implies that informed trading often take place from 11:30 a.m. to 2:00 p.m., which is consistent with Cornell and Sirri (1992) and Blau et al. (2009). Spread is superior to firm size and trading volume as a proxy for information asymmetry.

Keywords: stealth trading, order imbalance, return-order imbalance relation, information asymmetry.
JEL Classification: G1, G14.

Introduction

Informed investors attempt to camouflage their private information with liquidity traders by spreading trades over time (Kyle, 1985). Thus, large shares are likely to be broken into medium shares. Some literature indicates that informed traders concentrate their trades in the medium size category (500 to 9900 shares). In Cornell and Sirri's (1992) case study of an insider trading prosecution involving 38 traders, 78.2% of the insider trades are of medium size, compared with only 38.4% of all trades in the same stock. Barclay and Warner (1993) document that if stock price movements are due mainly to private information revealed through these investors' trades and if privately informed traders concentrate their trades of certain sizes – not too small (too expensive in terms of trading costs) and not too large (which could give them away) – then most of the stocks' cumulative price change will take place on medium-size trades. They label this joint hypothesis as the stealth hypothesis. In this paper, I explore whether the intraday return – order imbalance relation in the medium size are more significant than that in other size categories. In addition, Blau et al. (2009) use the concept of weighted price contribution (WPC)[1] proposed by Barclay and Warner (1993) to argue that price changes from smaller trades are higher during the middle of the day because informed investors break up their trades to disguise their information when intraday volume is low[2]. I use the impact of order imbalance on return to infer when the stealth trading often take place during the day.

Chae (2005) shows that trading volume decreases prior to earning announcements, implying that uninformed investors avoid trading when there is a high level of ex ante information asymmetry. In addition, since the extent of stealth trading is associated with trading volume (Blau et al., 2009), there should be some connection between information asymmetry and stealth trading. To know whether information asymmetry has a significant influence on return-order imbalance relation to stealth trading, I need a measure of information asymmetry. Since information asymmetry is not directly observable, a suitable proxy is necessary. Llorente et al. (2002) use firm size and bid-ask spread to measure information asymmetry. They argue that firms with larger size or smaller spread 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. A portion of the market maker's spread may be viewed as compensation for taking the other side of potential information-based trades. As a result, the firms with smaller information asymmetry would have smaller bid-ask spread. Easley et al. (1996) show that private information is more important 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

[1] Chakravarty (2001), Huang (2002), Cai et al. (2006), and Hansch and Choe (2007) also use WPC to explore stealth trading. Although other measures of informed trading (such as the information share and the common factor weights) exist, Huang (2002) argues that the WPC is preferred to other measures because of its flexibility in cross-sectional analyses.

[2] Moreover, price changes from larger trades are likely higher at the beginning and end of the day because high volume allows informed investors to increase their trade size without revealing their information to the market.

higher probability of informed trading. In this paper, I examine which is better as a proxy of information asymmetry among firm size, trading volume and spread.

Many researches investigate the relation between trading volume and return dynamics. Although volume is an important linkage between stock return and trading activity (Karpoff, 1987), volume alone conceals some important information about trading (Chan and Fong, 2000). Order imbalances convey more information than volume does. A large order imbalance has a great impact on price movement (Marsh and Rock, 1986; Lee, 1992; Madhavan and Smidt, 1993; Stoll, 2000; Chordia and Subrahmanyam, 2002; Su et al., 2010), 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[1] (Stoll, 1978; Ho and Stoll, 1983; Spiegel and Subrahmanyam, 1995).

In this paper, I find that the effects in the medium size are more significant than that in other sizes, which is consistent with stealth trading hypothesis. Since the contemporaneous return-order imbalance effect is the greatest from 11:30 a.m. to 2 p.m., informed trading often take place in this sub-period, which is consistent with Cornell and Sirri (1992) and Blau et al. (2009). Moreover, spread is superior to firm size and trading volume as a proxy for information asymmetry.

The rest of this paper is organized as follows. Section 1 describes data and methodology. In Section 2, I discuss empirical results. The last Section concludes.

1. Data and methodology

1.1. Data. 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, I use the 90-second cumulative transaction data[2]. I use the New York stock exchange (NYSE) trades and automated quotations (TAQ) databases from December 1, 2003 to December 31, 2003 as a sample. Quotes established before the opening of the market or after the close are discarded. Negative bid-ask spread quotations are discarded. Following Lee and Ready (1991), any quote less than five seconds prior to the trade is ignored and the first one at least five seconds prior to the trade is retained. I then sign trades using Lee and Ready (1991) rule: if a transaction occurs above (under) the prevailing quote midpoint, it is regarded as a buy (sell) order. If a transaction occurs exactly at the quote midpoint, it is signed using the previous transaction price according to the tick test (i.e., buys if the sign of the last non-zero price change is positive and vice versa).

I choose NASDAQ-100 component stocks as our sample for these stocks are traded frequently, efficiently in the deep and liquid market. The NASDAQ-100 Index includes one hundred stocks of the largest American and international non-financial companies listed on the NASDAQ stock market based on market capitalization. The Index reflects companies across major industry groups including computer hardware and software, telecommunications, retail/wholesale trade and biotechnology. It does not contain financial companies including investment companies. It is the largest U.S. electronic stock market and trades more shares per day than any other U.S. market. According to strict listing criteria on NASDAQ-100, I can see the excellent liquidity of these sample stocks.

For each stock, I define the order imbalance as follows. OINUM is the number of buyer-initiated trades minus that of seller-initiated trades, OISHA is the share of buyer-initiated trades minus that of seller-initiated trades and OIDOL is the dollar volume of buyer-initiated trades minus that of seller- initiated trades.

Table 1 presents the various definitions of trade size categories in many previous studies. Some of them use absolute shares to define sizes, whereas some of them use percentiles. According to Barclay and Warner (1993), Chakravarty (2001), Alexander Peterson (2007), and Hansch and Choe (2007), I divide all the data into three trade size categories: small (fewer than 500 shares), medium (500-9900 shares) and large (10000 and more shares). I ignore small trade size categories because the traders with valuable private information seem unlikely to limit their trading to small position to get small profit and there are a few informed trading in this area. Besides, the individual traders with finite budget constraints would take position of medium size and institutional investors without such a consideration would take large share position. Thus, I explore the effects in all, medium and large trade size categories.

Table 1. The definitions of trade size categories in previous studies

Authors and year of study	Trade size categories
Barclay and Warner (1993), Chakravarty (2001), Alexander and Peterson (2007), Hansch and Choe (2007)	Small (fewer than 500 shares) Medium (500-9900 shares) Large (10000 and more shares)

[1] The market makers would revise the price downward (upward) when there are excess sell (buy) orders.

[2] Lee et al. (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.

Table 1 (cont.). The definitions of trade size categories in previous studies

Authors and year of study	Trade size categories
Lin et al. (1995)	Less than 25 percent 25-50 percent 50-75 percent 75-90 percent 90-95 percent 95-99 percent Greater than 99 percent
Easley et al. (1997)	Small (fewer than 1000 shares) Large (at least 1000 shares)
Bessembinder and Kaufman (1997)	Small trade (less than $10000) Medium trade ($10000 - $199999) Large trade (above $200000)
Chan and Fong (2000)	Size 1: less than or equal to 500 shares Size 2: 501-1000 shares Size 3: 1001-5000 shares Size 4: 5001-9999 shares Size 5: 10000 shares and above
Lee and Yi (2001)	Stock: ♦ Small (fewer than 1000 shares); ♦ Large (at least 1000 shares). Option: ♦ Small (fewer than 10 contracts); ♦ Large (at least 1000 contracts).
Anand, and Chakravarty (2007)	Option: ♦ Small (fewer than 5 contracts); ♦ Medium (5-99 contracts); ♦ Large (at least 100 contracts).

Panel A of Table 2 presents the descriptive statistics of buyer-(seller)-initiated trades and order imbalances among NASDAQ-100 component stocks. I find that the mean of OISHA is 0.24 percent of total shares. The mean of OIDOL is -0.40 percent of total dollar volumes. From above, the means of OISHA is positive, indicating that investors' intention to buy stocks is greater than that to sell stocks, whereas the means of OIDOL is negative, implying that the average price of stocks bought is lower than that sold.

The means and standard deviations of buy and sell orders per trade are presented in Panel B of Table 2. The mean of OISHA per buy trade is 857.03 and that of per sell trade is -852.82, indicating that the shares is higher and the stock price is higher when investors buy stocks than those when they sell stocks.

Panel C presents the intraday trading during the day. I divide the whole day into three sub-periods: sub-period 1 (9:30-11:30 a.m.), sub-period 2 (11:30 a.m.-2:00 p.m.) and sub-period 3 (2:00 p.m.-4:00 p.m.). In order to ensure there are sufficient observations for model estimation in each sub-period, I consider those stocks whose number of transaction is at least sixty thousand during the sample period. These criteria reduce the sample to 12 stocks. Three definitions of order imbalance are positive in every sub-period, indicating that buy orders always surpass sell orders. Besides, the order imbalances in sub-period 2 are much lower than those in sub-periods 1 and 3, implying that investors' intention to buy stocks is the lowest in sub-period 2. The number of trading volume is the highest in the sub-period 1 and that is the lowest in the sub-period 2. It shows the same results by the shares and the dollar values of trading volume. Therefore, U-shaped intraday trading volume pattern[1] exist in our dataset.

Table 2. Descriptive statistics of buy/sell trades and order imbalances

Panel A. Numbers of trades and orders			
	Maximum	Minimum	Mean
Number of buy shares	1252200	1	857.03
Number of sell shares	2354500	100	852.82
OISHA/total trades (%)	-30.56	-98.02	0.24
Number of buy dollars	30269180	34	24282.25
Number of sell dollars	162776768	320	24087.04
OIDOL/total orders (%)	68.64	-80.60	-0.40

Panel B. Means and standard deviations of order per trade				
	Maximum	Minimum	Mean	S.D.
OISHA per buy trade	1252200	1.00	857.03	3657.99
OISHA per sell trade	-2354500	-100.00	-852.82	4004.13
OIDOL per buy trade	30269180	34.37	24282.25	91963.53
OIDOL per sell trade	-162776768	-320	-24087.04	128802.21

Panel C. Means of order imbalances and trading volumes per hour during the day						
Time of day	OINUM	OISHA	OIDOL	VOLNUM	VOLSHA	VOLDOL
Sub-period 1	35.14	71426.14	2430951.38	834.83	1481655.51	46369199.00
Sub-period 2	12.53	19145.30	769132.72	449.16	741692.92	22408538.67
Sub-period 3	35.22	72139.29	2302042.14	669.24	1198868.83	36412223.63

[1] Based on Jain and Joh (1988) and Chan et al. (1995), the heavy trading takes place in the beginning and the end of the day, while the relatively light trading occur in the middle of the day.

1.2. Methodology. According to the dynamic return-volume relation of individual stock on Llorente et al. (2002), I develop a regression model. Moreover, I add contemporaneous and lag-one order imbalance to catch the lead lag effect. The GARCH (1,1) model is employed to capture the time variant property of stock returns. In addition, Chan and Fong (2000) find order imbalance play a role in the volatility-volume relation. Therefore, I let lag-one order imbalance be the independent variable of error's variance.

A time varying GARCH (1,1) model describes as follow:

$$R_{it} = \alpha_0 + \alpha_1 OI_{it} + \alpha_2 OI_{it-1} + \alpha_3 R_{it-1} + \\ + \alpha_4 OI_{it-1} R_{it-1} + \xi_{it}, \tag{1}$$

$$\xi_{it} \sim N(0, h_{it}),$$

$$h_{it} = \beta_0 + \beta_1 h_{it-1} + \beta_2 \xi_{it-1}{}^2 + \beta_3 OI_{it-1}, \tag{2}$$

where R_{it} is the return of stock i in period t on event day, P_{it} is the transaction price[1], h_t is the conditional variance. OI_t is the order imbalance in period t. The parameter α_1 measures the contemporaneous order imbalance-return effect, the parameter α_2 measures the lag-one order imbalance-return effect, the parameter α_3 measures the effect of return autocorrelation, the parameter α_4 measures the effect of order imbalance on the autocorrelation of stock returns, the parameter β_3 measures the volatility – order imbalance effect.

Besides, according to Chordia and Subrahmanyam (2004), I develop a GARCH (1,1) model. Following Jones et al. (1994), return volatility of individual stock is estimated from the absolute residuals of the following model:

$$R_{it} = \gamma_0 + \varepsilon_{it}, \tag{3}$$

$$\varepsilon_{it} \sim N(0, h_{it}),$$

$$h_{it} = \phi_0 + \phi_1 h_{it-1} + \phi_2 \varepsilon_{it-1}{}^2, \tag{4}$$

where R_{it} is the return of stock i, h_t is the conditional variance. To examine the return-order imbalance relation, I estimate the following regression model:

$$R_{it} = \alpha_0 + \alpha_1 OI_{it} + \alpha_2 OI_{it-1} + \alpha_3 \theta_i + \xi_{it}, \tag{5}$$

$$\xi_{it} \sim N(0, h_{it}),$$

$$h_{it} = \beta_0 + \beta_1 h_{it-1} + \beta_2 \xi_{it-1}{}^2 + \beta_3 |\varepsilon_{it-1}| + \beta_4 |OI_{it-1}|, \tag{6}$$

where θ_{it} is the market premium[2] of stock i on the day t, OI_t is the order imbalance in period t, $|\varepsilon_t|$ is the return volatility and h_t is the conditional variance in period t. The parameter α_1 measures the contemporaneous return-order imbalance effect, the parameter α_2 measures the lag-one return-order imbalance effect, the parameter α_3 measures return-market premium effect, the parameter β_3 measures the volatility-market premium effect and the parameter β_4 measures the volatility-order imbalance effect.

Moreover, based on Chordia and Subrahmanyam (2004), I add trading volumes as the independent variables to examine whether the impact of order imbalance on return is stronger than that of trading volume does.

$$\alpha_{i1} = a + b_{i1} CAP_i + b_{i2} VOL_i + b_{i3} SPR_i, \tag{7}$$

where R_{it} is the return of stock i, OI_t is the order imbalance in period t, V_t is the trading volume in period t. Besides, I run the same regression as in equation (7), but omit the contemporaneous order imbalance and trading volume, and include five lags of order imbalance and trading volume to explore whether there is a predictive relation among returns, order imbalance and trading volume when contemporaneous variables are not included in the regression.

$$R_t = \alpha_0 + \alpha_1 OI_{t-1} + \alpha_2 OI_{t-2} + \alpha_3 OI_{t-3} + \alpha_4 OI_{t-4} + \\ + \alpha_5 OI_{t-5} + \beta_1 V_t + \beta_2 V_{t-2} + \beta_3 V_{t-3} + \beta_4 V_{t-4} + \beta_5 V_{t-5}. \tag{8}$$

Llorente et al. (2002) use firm size to measure information asymmetry. They argue that firms with larger size have a lower degree of information asymmetry. Easley et al. (1996) show that low volume stocks have a higher probability of informed trade. The greater price effects are associated with the greater risk of informed trading in such stocks. Llorente et al. (2002) find that higher degree of information asymmetry is associated with greater opening spread. I use the following model to examine the relation among three proxies of information asymmetry and the contemporaneous return-order imbalance effect.

$$\alpha_{i1} = a + b_{i1} CAP_i + b_{i2} VOL_i + b_{i3} SPR_i, \tag{9}$$

where α_{i1} is the contemporaneous return-order imbalance effect of stock i, CAP_i is the firm size of stock i, VOL_i is the average daily trading volume of past three month of stock i, SPR_i is the average spread of opening thirty minutes of stock i.

2. Empirical results

Table 3 presents the relation among stock returns, order imbalances and volatility in the 90-second

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

[2] We use daily return of each stock on event day as market premium of each stock.

time interval. Panels A and B show that the contemporaneous order imbalance-return effect is positive and significant for virtually all the firms, whereas the lag-one order imbalance-return effect is positive for approximately all the firms, with 47% of the effect is significant. The contemporaneous effect is in a manner consistent with both the inventory and asymmetry information effects of price formation. The lag-one effect indicates that although the new information is almost reflected to stock price in the current 90 seconds, there is still some information revealed by stock price in the subsequent 90 seconds. Besides, "percent positive and significant" in medium size is higher than that in large size. It indicates that the contemporaneous effects in the medium size are more significant than that in other sizes, which is consistent with stealth trading hypothesis.

Table 3. The relation among stock returns, order imbalance and volatility

	Average coefficient	Percent positive	Percent positive and significant	Percent negative and significant
Panel A. The contemporaneous imbalance-return effect				
All trade size	0.0005***	84.00	82.00	14.00
Large trade size	0.0014***	91.11	87.78	7.78
Medium trade size	0.0028***	90.00	90.00	9.00
Panel B. The Lag-one order imbalance-return effect				
All trade size	0.0007	99.00	47.00	0.00
Large trade size	0.0013***	97.78	43.33	0.00
Medium trade size	0.0015***	95.00	40.00	0.00
Panel C. The effect of return autocorrelations				
All trade size	0.0605	96.00	20.00	0.00
Large trade size	0.0844***	97.78	27.78	0.00
Medium trade size	0.3063***	98.00	43.00	0.00
Panel D. The effect of order imbalance on the autocorrelation of stock returns				
All trade size	0.0002	96.00	61.00	0.00
Large trade size	0.0047***	96.67	50.00	0.00
Medium trade size	0.0001***	97.00	63.00	0.00
Panel E. The volatility-order imbalance effect				
All trade size	0.0113	99.00	70.00	0.00
Large trade size	0.0103***	95.56	35.56	0.00
Medium trade size	0.1021***	100.00	59.00	0.00

Notes: ***, **, and * denote significant at 1%, 5%, and 10% level. "Significant" denotes significant at the 5% level.

In Panels C and D, I report that virtually all the coefficients are positive, indicating that speculative trades dominate hedging trade in the light of Llorente et al. (2002). They argue that speculative trades generate positively auto-correlated returns and hedging trades create negatively auto-correlated returns. For instance, when investors buy stocks for speculative reason, the price will increase, reflecting the positive private information about its future payoff. The high return in the current period will be followed by the high return in the subsequent period for the information is partially impounded into the current price. Nonetheless, when investors buy stocks for hedging reason, the price will increase to attract others to sell. Owing to the same expectation of future payoff, the increase in the price results in a high return in the current period and a low expected return for the subsequent period. Moreover, the "percent positive and significant" in medium size is still higher than that in large size, indicating that the effect of return autocorrelations and effect of order imbalance on the autocorrelation of stock returns in the medium size are more significant than those in other sizes.

Panel E shows that the volatility-order imbalance effects are virtually positive, with 50% of the effect is significant. Chan and Fong (2000) find that after controlling for the return impacts of order imbalance, the volatility-volume relation becomes much weaker, suggesting that the daily return impact of order imbalance is a significant determinant of the volatility-volume relation. Our results are in a manner consistent with Chan and Fong (2000). Besides, the volatility-order imbalance effect in the medium size is more significant than that in other sizes.

Overall, in the context of the "percent positive and significant", the influence of contemporaneous order imbalance-return effect is the greatest among the above effects, the impact of the effect of return autocorrelation is the smallest, and the volatility-order imbalance effect is between them.

Owing to the strongest effects in medium size, I focus on the effects in medium size. Table 4 presents the relation among stock returns, order imbalances, market premium and volatility using a GARCH (1,1) model in medium size. The results show that the contemporaneous order imbalance-return effect is positive for virtually all the firms, with 72% of the effect is significant, whereas about 50% of the lag-one order imbalance-return effect is positive, with 38% of the effect is significant. The contemporaneous effect is still virtually consistent with both the inventory and asymmetry information effects of price formation. The lag-one effect still indicates, there is some information revealed by stock price in the subsequent 90 seconds.

Table 4. The relation among stock returns, order imbalance and expected stock returns in medium trade size category

	Average coefficient	Percent positive	Percent positive and significant	Percent negative and signeficant
OI_{it}	0.1226** (2.65)	100.00	72.00	0.00
OI_{it-1}	0.0983*** (2.92)	50.00	38.00	0.00
θ_i	0.0438 (1.57)	76.47	55.88	0.00
$\lvert\varepsilon_{it-1}\rvert$	0.0040 (1.43)	0.00	0.00	0.00
$\lvert OI_{it-1}\rvert$	0.0040 (1.43)	0.00	0.00	0.00

Note: ***, **, and * denote significant at 1%, 5%, and 10% level. "Significant" denotes significant at the 5% level.

In addition, I report that about 77% of the coefficients of market premium are positive, with about 56% is significant, indicating that market premium has a great impact on the stock return. The coefficients of absolute value of market premium and order imbalance on the return volatility are 0.00 percent significant.

In Table 5, I include the contemporaneous order imbalance, four lags of order imbalance, contemporaneous trading volume and four lags of trading volume in the time-series return regressions during the day. Panel A shows that the contemporaneous order imbalance-return effect is positive and significant for all the firms, whereas 83.33% of the lag-one order imbalance-return effect is negative, with 25% of the effect is significant. The results are consistent with the results of Chordia and Subrahmanyam (2004), who indicate that the negative coefficient on lagged order imbalance arises because of the over-weighting of history-dependent trades in the current order imbalance.

Table 5. The relation among stock returns, order imbalance and trading volume in medium trade size category during the day

	Average coefficient	Percent positive	Percent positive and significant	Percent negative and signeficant
Panel A. All periods				
OI_t	0.00117722*** (5.28)	100.00	100.00	0.00
OI_{t-1}	-0.00005617 (-1.63)	16.67	0.00	25.00
OI_{t-2}	0.00001293* (-0.33)	33.33	16.67	8.33
OI_{t-3}	0.00001293* (0.36)	41.67	8.33	0.00
OI_{t-4}	-0.00003556 (-1.67)	33.33	0.00	0.00
Panel B. OI_t				
Sub-period 1	0.00117722*** (5.28)	100.00	100.00	0.00
Sub-period 2	0.00130992*** (4.93)	100.00	100.00	0.00
Sub-period 3	0.00114921*** (5.74)	100.00	100.00	0.00
Panel C. VOL_t				
Sub-period 1	0.00011697 (1.00)	66.67	50.00	16.67
Sub-period 2	-0.00000652 (-0.10)	33.33	8.33	25.00
Sub-period 3	-0.00002426* (-1.96)	33.33	0.00	8.33

Note: ***, **, and * denote significant at 1%, 5%, and 10% level. "Significant" denotes significant at the 5% level.

The volume-return effects are all insignificant (not reported for brevity). Panel B presents that the average coefficients of contemporaneous order imbalance (percentage positive and significant) are 0.0011 (100.00), 0.0013 (100.00) and 0.0011 (100.00) in the sub-periods 1, 2 and 3, respectively. Panel C exhibits that the average coefficients of contemporaneous trading volume (percentage positive (negative) and significant) are 0.0001 (50.00), -0.0000 (25.00) and -0.0000 (8.33) in the sub-periods 1, 2 and 3, respectively. The results show that the impact of order imbalance on return is stronger than that of trading volume, implying that order imbalance indeed convey more information than trading volume does. The average coefficients on the lagged order imbalances are virtually negative, indicating that auto-correlated order imbalances result in the effect of the lagged order imbalance to be reversed out in the contemporaneous return. Moreover, the contemporaneous order imbalance-return effect is the greatest in the sub-period 2, implying that informed trading often take place from 11:30 a.m. to 2:00 p.m., which is consistent with Cornell and Sirri (1992) and Blau et al. (2009).

Besides, I omit the contemporaneous order imbalance and trading volume, and include five lags of order imbalance and trading volume. The results (not reported for brevity) presents that virtually all the coefficients are insignificant, indicating that lagged order imbalances and trading volumes have insignificant predictive power for returns.

In Table 6, I use the firm size, average daily trading volume of past three months and the average spread of opening thirty minutes as proxies for information asymmetry to examine three contemporaneous order imbalance-return effect, which result from GARCH (1,1) and OLS regression models. The coefficients are virtually significant in OLS regression model, whereas those are virtually insignificant in GARCH (1,1) model. The results in OLS regression model show that there is negative relation between contemporaneous order imbalance-return effect and trading volume, which is consistent with the result of Easley et al. (1996) and positive relation between contemporaneous order imbalance-return effect and spread, which is consistent with the result of Llorente et al. (2002). Besides, spread is superior to firm size and trading volume as a proxy for information asymmetry for spread is more significant than others in OLS model.

Table 6. The relation among the order imbalance-return effect, firm size, average daily trading volume of past three months and the average opening spread

Model	1	2	3	4	5	6	7
Panel A. GARCH (1,1)							
b_1	-0.0001 (-0.13)			0.0008 (0.59)	0.0003 (0.30)		0.0010 (0.71)
b_2		-1.78E-9 (-0.68)		-3.61E-9 (-0.89)		-8.96E-10 (-0.30)	-2.94E-9 (0.71)
b_3			18.99 (0.89)		22.15 (0.93)	15.63 (0.65)	18.42 (0.75)
Adj. R^2 (%)	0.02	-0.55	-0.21	-1.22	-1.15	-1.15	-1.67
Panel B. OLS							
b_1	-0.0000*** (-5.53)			-0.0000 (-0.94)	-0.0000*** (-2.68)		6.46E-7 (0.15)
b_2		-7.12E-11*** (-6.97)		-6.00E-11*** (-3.83)		-3.64E-11*** (-4.19)	-3.77E-11*** (-3.09)
b_3			0.7455*** (11.02)		0.6584*** (8.99)	0.6089*** (8.62)	0.6106*** (8.49)
Adj. R^2 (%)	22.98	32.47	54.86	32.38	57.55	61.38	60.99

Note: ***, **, and * denote significant at 1%, 5%, and 10% level.

Conclusion

In this study, I employ GARCH (1,1) and OLS models, which are based on Llorente et al. (2002), and Chordia and Subrahmanyam (2004) to examine the return-order imbalance relation to stealth trading in the NASDAQ-100 component stocks.

The conclusions are as follows. The contemporaneous order imbalance-return effects are positive and significant in every model. Besides, the effects in the medium size are more significant than that in other size categories, which is consistent with stealth trading hypothesis. The lag-one order imbalance-return effect is negative in OLS model, whereas that is positive in GARCH (1,1) model. The impact of order imbalance on return is stronger than that of trading volume, implying that order imbalance convey more information than trading volume does. The contemporaneous order imbalance-return effect is the greatest in the sub-period 2. It implies that informed trading often take place from 11:30 a.m. to 2:00 p.m., which is consistent with Cornell and Sirri (1992) and Blau et al. (2009). Moreover, spread is superior to firm size and trading volume as a proxy for information asymmetry.

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