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INTRADAY RETURN-ORDER IMBALANCE RELATION IN NASDAQ SPECULATIVE NEW LOWS

Yong Chern Su, Han Ching Huang

Abstract

This paper explores the dynamic relation between intraday return and order imbalance on extraordinary events. We examine the relation during the day when the speculative stocks reach 52-week new low records. In this study, we employ an EGARCH (1,1) model based on the argument of return-order imbalance relation of individual stocks (Chordia & Subrahmanyam, 2004) to test whether the volatility stems from order imbalance. We find intraday volatility is not associated with market premium and order imbalance. The contemporaneous return-order imbalance effect is significant in the third period time regime. It implies that informed trading takes place from 2 P.M. to 4 P.M. The impact of the trading volume on the order imbalance-return effect is weaker than that of the firm size.

Key words: order imbalance; return-order imbalance relation; new low; information asymmetry.

JEL classification: G12, G13.

1. Introduction

A lot of literature investigates 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 & Fong, 2000). For example, given a reported volume of 100,000 shares, there are many possible situations. It might be 50,000 seller-initiated shares and 50,000 buyer-initiated shares. In 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 does. Stock price has a strong relation with order imbalance. A large order imbalance has a great impact on price movement, 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 & Stoll, 1983; Spiegel & Subrahmanyam, 1995). 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 firms is higher than that in smaller ones. Easley, Kiefer, O'Hara and Paperman (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 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 imbal-

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

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ances. 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 put emphasis on examining the relation between intraday return and order imbalance in the speculative stocks listed on NASDAQ with top 10 declining ratio.

Although Chan and Fong (2000) find order imbalances play a role in the volatility-volume relation, we use an asymmetrical EGARCH (1,1) model to examine the return-volatility-order imbalance relationship. The above literature uses the firm size and trading volume as proxies of information asymmetry separately, whereas we define a ratio of trading volume to firm size to see which proxy is better. In addition, Cornell and Sirri (1992) find insider trading often takes 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 takes place during the day.

In this paper, we find that the volatility is due to asymmetrical model structure itself instead of market premium and order imbalance, for the coefficients of absolute value of market premium and order imbalance on the return volatility are 0.00 percent significant. Besides, the firm size is better than the trading volume as a proxy of information asymmetry, because the impact of the firm size on the order imbalance-return effect is stronger than that of the trading volume. Moreover, informed trading often takes place from 2:00 P.M. – 4:00 P.M. for the contemporaneous return-order imbalance effect 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.

2. Data and Methodology

2.1. Data

2.1.1. 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[1], 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. Our sample period is from Oct. 2004 to Mar. 2005. These data are available on the Island-ECN website[2], which 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. Moreover, ECN provides extended transactions before and after market. For instance, as compared to normal market from 9:30 A.M. to 4:00 P.M., Island-ECN provides service from 8 A.M. to 8 P.M. In addition, Barclay, Hendershott and Mccormick (2003) find ECN offers the advantages of anonymity and speed of execution, which attract informed traders. Thus, trades are more likely to occur on ECN when information asymmetry is greater and when trading volume and stock-return volatility are higher. There is more private information revealed through ECN trades than through market maker trades. As a result, we choose an information transparently provided ECN-Island, as our data source.

We 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 ma-

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[1] 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.

[2] 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.

jor 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, we can see the excellent liquidity of these sample stocks.

Stocks are included or excluded depending on the following criteria:

1. We select the speculative stocks that reach 52-week new low records on each transaction day as our samples. The purpose of this study is to examine the relation between return and order imbalance among these speculative stocks.
2. Eliminate the speculative stocks with intraday trading volume below 1 million shares. Order imbalance is used as a proxy to the extent of information asymmetry while analyzing its effects on individual stock returns. In addition, trading volume implies exchange frequency of different information among traders. Thus, trading volume should be large enough for observing information asymmetry phenomenon. This study chooses 1 million shares as lower limit of trading volume.
3. Omit repetitive individual stocks. Because sample period is across several days, the sampling procedure cannot prevent the problem that the same individual stock is sampled twice or more. In order to clearly understand the effects of order imbalance on trading volume and generalize these effects to analyze the discretionary stock, only one set of transaction data for each individual stock is retained.

For each stock, we define the order imbalance as follows:

OINUM: the number of buyer-initiated trades minus that of seller-initiated trades.

OISHA: the share of buyer-initiated trades minus that of seller-initiated trades.

OIDOL: the dollar volume of buyer-initiated trades minus that of seller-initiated trades.

2.1.2. 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 OINUM is 0.06 percent of total trades. The mean of OISHA is 0.04 percent of total shares. The mean of OIDOL is 0.06 percent of total dollar volumes. From above, we know that the means of three definitions 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 OISHA (OIDOL) per buy trade is 199.77 (2565.86) and that of sell orders per trade is -209.90(-2594.64), indicating that the shares is higher and the stock price is higher when investors sell stocks than those when they buy stocks.

Table 1

Descriptive Statistics of Buy/Sell Trades and Order Imbalances

Panel A: Numbers of trades and orders			
	Maximum	Minimum	Mean
Number of buy trades	2319	81	707.96
Number of sell trades	2728	45	616.41
OINUM/Total trades(%)	-0.08	0.28	0.06
Number of buy shares	392605	11801	133870
Number of sell shares	480560	8900	121973
OISHA/Total trades(%)	-0.10	0.14	0.04
Number of buy dollars	12304831	22214	1719399
Number of sell dollars	15273533	14755	1507692
OIDOL/Total orders(%)	-0.10	0.20	0.06

Tabel 1 (continuous)

Panel B: Means and standard deviations of order per trade				
	Maximum	Minimum	Mean	S.D.
OISHA per buy trade	8300.00	1.00	199.77	203.05
OISHA per sell trade	-44100.00	-1.00	-209.90	348.56
OIDOL per buy trade	177525.00	3.06	2565.86	4052.02
OIDOL per sell trade	-154960.00	-2.56	-2594.64	3511.46

2.2. Methodology

According to the return-order imbalance relation of individual stock on Chordia and Subrahmanyam (2004), we develop a regression model. The EGARCH (1,1) model is employed to test whether order imbalances play a role in the volatility-volume relation (Chan & Fong, 2000).

Following Jones, Kaul and Lipson (1994), return volatility of individual stock is estimated from the absolute residuals of the following model:

$$R_{it} = \gamma_0 + \varepsilon_t \tag{1}$$

$$\varepsilon_t \sim N(0, h_t) ,$$

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

where R_{it} is the return of stock i in period t on event day, defined as $\ln(P^1{}_t / P_{t-1}) * 10000$, h_t is the conditional variance. To examine the return-order imbalance relation, we estimate the following regression model:

$$R_{it} = \alpha_0 + \alpha_1 OI_t + \alpha_2 OI_{t-1} + \alpha_3 \theta_t + \xi_t \tag{3}$$

$$\xi_t \sim N(0, h_t) ,$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \xi_{t-1}{}^2 + \beta_3 |\varepsilon_{t-1}| + \beta_4 |OI_{t-1}| , \tag{4}$$

where θ_{it} is the market premium[2] of stock i on event 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.

Llorente et al. (2002) and Lo and MacKinlay (1990) use firm size to measure information asymmetry. They argue that firms with larger size have a lower degree of information asymmetry. We use the same proxy in our empirical analysis. To see whether order imbalances for large firm arise less stock returns, a regression test is adopted as follows:

$$\alpha_i = \alpha_0 + \alpha_1 Z_i , \tag{5}$$

where α_i : the contemporaneous return-order imbalance effect of stock i ,

Z_i: the firm size of stock i.

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. We use the following model to examine the relation between volume and shadow price.

$$\alpha_i = \alpha_0 + \alpha_1 V_i , \tag{6}$$

where α_i : the contemporaneous return-order imbalance effect of stock i,

V_i: the average daily trading volume of past three months of stock i.

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[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.

3. Empirical Results

In Table 2, we present the relation among stock returns, order imbalances, market premium and volatility. Panel A exhibits the outcomes for share imbalances, while Panel B presents the results for dollar imbalances. In Panel A, we show that the contemporaneous order imbalance-return effect is positive for virtually all the firms, with 80.00% of the effect is significant, whereas the lag-one order imbalance-return effect is positive for about 86.00% of the firms, with about 32.00% 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 is weakly consistent with the aforementioned finding, implying that the new information is almost fully reflected to stock price in the current 90 seconds and little revealed by stock price in the subsequent 90 seconds.

Table 2

The Relation among Stock Returns, Order Imbalance and Market Premium

	Average coefficient	Percent positive	Percent positive and significant	Percent negative and significant
Panel A: OISHA				
$OISHA_{it}$	0.1402*** (2.76)	100.00	80.00	0.00
$OISHA_{it-1}$	0.1008*** (2.21)	86.67	32.00	0.00
θ_i	0.0034* (1.55)	94.67	37.33	0.00
$\lvert \varepsilon_{it-1} \rvert$	0.0000* (1.34)	26.67	0.00	0.00
$\lvert OI_{it-1} \rvert$	0.0030* (1.43)	36.00	0.00	0.00
Panel B: OIDOL				
$OIDOL_{it}$	0.4292*** (3.50)	98.67	84.00	0.00
$OIDOL_{it-1}$	0.1409*** (3.47)	72.00	33.33	0.00
θ_i	0.0544* (1.49)	97.33	25.33	0.00
$\lvert \varepsilon_{it-1} \rvert$	0.0053* (1.43)	16.00	0.00	0.00
$\lvert OI_{it-1} \rvert$	0.0053* (1.43)	21.33	0.00	0.00

"Significant" denotes significance at the 5% level (two-tailed test). Significance levels of 10% , 5% and 1% are indicated by *, ** and *** respectively. The t-statistics appear in parentheses.

In addition, we report that almost all the coefficients of market premium are positive, with about 37.33% 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, implying that volatility is due to model structure itself instead of market premium and order imbalance.

The results in Panel B are similar to those in Panel A except that the contemporaneous order imbalance-return effect in Panel B is stronger than that in Panel A by average coefficient and "percent positive and significant".

Overall, in the context of the significance of average coefficient and "percent positive and significant", the influence of contemporaneous order imbalance-return effect is the greatest among the above effects, the return-market premium effect is the smallest, and the lag-one order imbalance-return effect is between them.

Table 3 presents the intraday trading during the event day. We divide the whole day into three periods: period 1 (09:30-11:30 A.M.), period 2 (11:30 A.M. – 2:00 P.M.) and period 3 (2:00 P.M. – 4:00 P.M.). In order to ensure there are sufficient observations for model estimation in each period, we consider those stocks whose number of transaction is at least three thousand during the event day. These criteria reduce the sample to 12 stocks. The number and share of order imbalance are positive in three periods except share of order imbalance in period 1 is negative, implying that when the speculative stocks reach 52-week new low records, sell orders surpass buy orders in the morning, but the situation is the opposite in the afternoon. Besides, OINUM and OISHA are both the highest in period 3. Therefore, the stocks always reach new low records in the morning and they would rebound in the afternoon. Moreover, the number of trading volume is the highest in period 1 and that is the lowest in period 2. It shows the same results by the shares of trading volume. Therefore, U shaped daily trading volume pattern[1] exists in our dataset.

Table 3

Means of Order Imbalances and Trading Volumes per Hour during the Day

Time of day	OINUM	OISHA	VOLNUM	VOLSHA
Period 1	36.30	-6881.43	556.70	109329.08
Period 2	3.88	1566.95	373.72	69453.70
Period 3	81.70	14537.25	535.10	97798.95

Table 4 presents the contemporaneous return-OISHA[2] effect in three time periods. The average coefficients (percentage positive and significant) are 0.1112 (90.00), 0.1272 (90.00) and 0.2618 (90.00) in period 1, period 2 and period 3, respectively. The contemporaneous order imbalance-return effect is the greatest in period 3, implying that informed trading often takes place in the afternoon. The above can be explained as follows. Insiders have the private information about where the new low price of the stock is, and buy stocks in the afternoon. Thus, the stock price makes new low in the morning and the order imbalance is the highest in the afternoon.

Table 4

The Relation during the Time of Day

	Average coefficient	Percent positive	Percent positive and significant	Percent negative and significant
Panel A: Period 1				
$OISHA_{it}$	0.1112 (1.21)	90.00	90.00	0.00
$OISHA_{it-1}$	0.1181 (1.30)	40.00	20.00	0.00
θ_i	0.0109*** (4.41)	80.00	70.00	0.00
Panel B: Period 2				
$OIDOL_{it}$	0.1272* (1.31)	100.00	90.00	0.00
$OIDOL_{it-1}$	0.537* (1.75)	60.00	30.00	0.00
θ_i	0.1206 (1.23)	100.00	100.00	0.00

[1] Trading is highest at the beginning and end of the day.
[2] The results are similar when we use OIDOL instead of OISHA.

Table 4 (continuous)

Panel C: Period 3				
OIDOL $_{it}$	0.2618* (2.09)	100.00	90.00	0.00
OIDOL $_{it-1}$	0.1086 (1.12)	30.00	10.00	0.00
θ_i	0.1147 (1.17)	90.00	80.00	0.00

"Significant" denotes significance at the 5% level. Significance levels of 10%, 5% and 1% are indicated by *, ** and *** respectively. The t-statistics appear in parentheses.

We divide all stocks into three groups according to their firm size, average daily trading volume of past three months and the ratio of trading volume to firm size as proxies for information asymmetry to examine the relation between firm size and the order imbalance-return effect. In Table 5, we examine the relation among firm size, average daily trading volume of past three months, the ratio of trading volume to firm size and the return-order imbalance effect by categorical analysis. For short, we only report the results by OISHA (The results are similar by OIDOL). Panel A presents that lower coefficient is virtually associated with lower firm size. The size-stratified results are in a manner not consistent with the results of Llorente et al. (2002). Panel B shows that the categorical analysis presents that lower coefficient is virtually associated with lower trading volume. The volume-stratified results are in a manner not consistent with the results of Easley et al. (1996). In order to know whether the firm size as a proxy of information asymmetry is stronger than the average daily trading volume of past three months, we use the ratio of trading volume to firm size (VOL/CAP) to test the order imbalance-return effect. Panel C presents that higher order imbalance-return coefficient is virtually associated with lower ratio. For the relations between firm size, trading volume and return-order imbalance effect are both positive and the relations between imbalance-return coefficient and the ratio (VOL/CAP) is negative, we conclude that the impact of the trading volume on the order imbalance-return effect is weaker than that of the firm size.

Table 5

The Categorical Analysis

The units of average number in Panels A, B and C are billion dollars, thousand shares and thousand shares by billion dollars. "Significant" denotes significance at the 5% level. Significance levels of 10%, 5% and 1% are indicated by *, ** and *** respectively. The t-statistics appear in parentheses.

	Average coefficient	Percent positive	Percent positive and significant	Average number
Panel A: Firm size				
Low (N=24)	0.0866 (1.51)	100.00	79.16	66.40
Medium (N=25)	0.1314* (2.00)	100.00	80.00	277.21
High (N=24)	0.1729** (2.24)	100.00	79.16	1211.09
Panel B: Average daily trading volume of past three months				
Low (N=24)	0.0538 (1.30)	100.00	83.33	1174.87
Medium (N=25)	0.1664** (2.24)	100.00	72.00	1603.40
High (N=24)	0.1691** (2.18	100.00	83.33	3001.79

Table 5 (continuous)

Panel C: The ratio of trading volume to firm size				
Low (N=24)	0.1747** (2.27)	100.00	83.33	2036.99
Medium (N=25)	0.0897 (1.63)	100.00	76.00	6848.59
High (N=24)	0.1282* (1.87)	100.00	79.16	1211.09

Table 6 presents the relation among the order imbalance-return effect, firm size, average daily trading volume of past three months and the ratio of volume to firm size using regression analysis. Panel A presents the results by OISHA, while Panel B presents the results by OIDOL. For the coefficients in Panel A which are virtually smaller than the corresponding numbers in Panel B, we use the results in Panel B to deduce the conclusion. Among the coefficients in Panel B, the t values of the firm size are the greatest, indicating that firm size is superior to average daily trading volume of past three months and the ratio of trading volume to firm size as a proxy of information asymmetry. Besides, the results in regression analysis are the same as those in categorical analysis.

Table 6

The Regression Analysis

This table provides an analysis using the following cross-sectional regression: $\alpha_1 = a + b_1*CAP + b_2*VOL + b_3*(VOL/CAP)$ where CAP is the firm size, VOL is the average daily trading volume of past three months and VOL/CAP is ratio of volume to firm size. As the coefficients of b_1, b_2 and b_3 are very small, we multiple the above coefficients by 10^7. Significance levels of 10%, 5% and 1% are indicated by *, ** and *** respectively. The t-statistics appear in parentheses.

Model	1	2	3	4	5	6	7
Panel A: OISHA							
b_1	296 (0.59)			132 (0.26)	405 (0.75)		0.00 (0.29)
b_2		0.66 (1.44)		0.63 (1.33)		0.66 (1.40)	0.60 (1.20)
b_3			5.23 (0.30)		10 (0.55)	0.33 (0.02)	2.82 (0.14)
R^2 (%)	0.49	2.84	0.13	2.93	0.92	2.84	2.96
Panel B: OIDOL							
b_1	2112 (2.97)***			1983 (2.70)***	1764 (2.32)**		1434 (1.78)*
b_2		0.93 (1.36)		0.49 (0.72)		1.28 (1.89)*	0.84 (1.09)
b_3			-55.3** (-2.19)		-33.1 (-1.25)	-64.8 (-2.56)**	-43.5 (-1.57)
R^2 (%)	11.00	2.53	6.32	11.7	1.11	10.8	14.7

4. 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 employ a model based on the argument of return-order imbalance relation of individual stocks (Chordia & Subrahmanyam, 2004). Since order imbalances play a role in the volatility-volume relation (Chan & Fong, 2000), we use an EGARCH (1,1) model to test whether the volatility stems from order imbalance.

The conclusions are as follows. The volatility is due to model structure itself instead of market premium and order imbalance. The contemporaneous order imbalance-return effect is the greatest in period 3, implying that informed trading often take place in the afternoon. The categorical and regression analyses show that there is a positive and significant relation between firm size and the order imbalance-return effect when we use OIDOL as the order imbalance. Besides, there is a positive and insignificant relation between trading volume and the order imbalance-return effect. Above all, the impact of the trading volume on the order imbalance-return effect is weaker than that of the firm size.

This research could extend to other extraordinary events such as the NASDAQ speculative top gainers (losers). In addition, the bid-ask spread could be used as a proxy of information asymmetry (Llorente, Michaely, Sarr, & Wang, 2002). Barclay and Warner (1993) find although the majority of trades are small, most of the cumulative stock price change is due to medium size trades. Therefore, if we focus on medium size trades, the above effects would be powerful.

References

1. Barclay, J., T. Hendershott, D. Mccormick. Competition among Trading Venues: Information and Trading on Electronic Communications Networks // Journal of Finance, 2003. – **№** 58. – pp. 2637-2666.
2. Blume, M., A. MacKinlay, B. Terker. Order Imbalances and Stock Price Movements on October 19 and 20, 1987 // Journal of Finance, 1989. – **№** 44. – pp. 827-848.
3. Chan, K., W. Fong. Trade Size, Order Imbalance, and the Volatility-Volume Relation // Journal of Financial Economics, 2000. – **№** 57. – pp. 247-273.
4. Chordia, T., R. Roll, A. Subrahmanyam. Order Imbalances, Liquidity, and market Returns // Journal of Financial Economics, 2002. – **№** 65. – pp. 111-130.
5. Chordia, T., A. Subrahmanyam. Order Imbalances and Individual Stock Returns: Theory and Evidence // Journal of Financial Economics, 2004. – **№** 72. – pp. 485-518.
6. Cornell, B., E. Sirri. The Reaction of Investors and Stock Prices to Insider Trading // Journal of Finance, 1992. – **№** 47. – pp. 103l-1059.
7. Cushing, D., A. Madhavan. Stock Returns and Trading at the Close // Journal of Financial Markets, 2000. – **№** 3. – pp. 45-67.
8. Easley, D., N.M. Kiefer, M. O'Hara, J. Paperman. Liquidity, Information, and Infrequently Traded Stocks // Journal of Finance, 1996. – **№** 51. – pp. 1405-1436.
9. Ekinci, C. A Statistical Analysis of Intraday Liquidity, Returns and Volatility of an Individual Stock from the Istanbul Stock Exchange // Working papers, 2004. Aix-Marseille III University
10. Hasbrouck J. Trades, Quotes, Inventories and Information // Journal of Financial Economics, 1988. – **№** 22. – pp. 229-252.
11. Ho, T., H. Stoll. The Dynamics of Dealer Markets under Competition // Journal of Finance, 1983. – **№** 38. – pp. 1053-1074.
12. Huang, R., H. Stoll. Market Microstructure and Stock Return Predictions // Review of Financial Studies, 1994. – **№** 7. – pp. 179-213.
13. Jones, C., G. Kaul, M. Lipson. Transactions, Volume, and Volatility // Review of Financial Studies, 1994. – **№** 7. – pp. 631-651.
14. Karpoff, J.M. The Relation between Price Changes and Trading Volume: A Survey // Journal of Financial and Quantitative Analysis, 1987. – **№** 22. – pp. 109-126.

15. Kyle, A.S. Continuous Auctions and Insider Trading // Econometrica, 1985. – **№** 53. – pp. 1315-1335.
16. Lauterbach, B., U. Ben-Zion. Stock Market Crashes and the Performance of Circuit Breakers: Empirical Evidence // Journal of Finance, 1993. – **№** 48. – pp. 1909-1925.
17. Lee, C. Earnings News and Small Traders: An Intraday Analysis // Journal of Accounting and Economics, 1992. – **№** 15. – pp. 265-302.
18. Lee, C., M. Ready. Inferring Trade Direction from Intraday Data // Journal of Finance, 1991. – **№** 46. – pp. 733-747.
19. Lee, T., R. Fok, Y. Liu. Explaining Intraday Pattern of Trading Volume from the Order Flow Data // Journal of Business Finance and Accounting, 2001. – **№** 28. – pp. 199-230.
20. Llorente, G., R. Michaely, G. Sarr, J. Wang. Dynamic Volume-Return Relation of Individual Stocks // The Review of financial studies, 2002. – **№** 15. – pp. 1005-1047.
21. Madhavan, A., S. Smidt. An Analysis of Changes in Specialist Inventories and Quotations // Journal of Finance, 1993. – **№** 48. – pp. 1595-1628.
22. Marsh, T.A., K. Rock. The Transaction Process and Rational Stock Price Dynamics // Working Paper, 1986. Haas School of Business, University of California, Berkeley.
23. Ronald L.G., A.P. Christine, R. Uday. Equilibrium in a Dynamic Limit Order Market // Journal of Finance, 2005. – **№** 60. – pp. 2146-2192.
24. Spiegel, M., A. Subrahmanyam. On Intraday Risk Premia // Journal of Finance, 1995. – **№** 50. – pp. 319-339.
25. Stoll, H. The Supply of Dealer Services in Securities Markets // Journal of Finance, 1978. – **№** 33. – pp. 1133-1151.
26. Stoll, H. Friction // Journal of Finance, 2000. – **№** 55. – pp. 1479-1514.