Order Imbalance, Individual Stock Returns and Volatility: Evidence from China

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Abstract

In this paper, we investigate the relationship between daily order imbalance and individual stock returns and volatility in Chinese stock market. The results show that contemporaneous order imbalance exerts an extremely significant impact on individual stock returns and volatility, but lagged order imbalance has no power of prediction for individual stock returns and volatility.

Keywords: *order imbalance, individual stock returns, volatility*

1. Introduction

The order imbalance, i.e., buyer-initiated orders less seller-initiated orders, could capture both the quantity and direction of trading activity, and has been the interest of many researchers and investors. Chan and Fong (2000) examine the role of order imbalances in explaining the volatility-volume relation for a sample of NYSE and NASDAQ stocks. Chordia et al. (2002) study market-wide order imbalance of S&P500 and find that order imbalance exerts a positive impact on contemporaneous market returns and volatility, and a negative impact on liquidity, but has no power of prediction for these three variables. Chordia and Subrahmanyam (2004) study the relation between order imbalance and daily returns of individual stocks, and find a positive relation between lagged imbalances and returns, which reverses sign after controlling for the current imbalances. Li et al. (2005) analyze the effect of order imbalances on the quotation behavior of NASDAQ market makers and find order imbalance affects only price movement, not spreads. Su et al. (2010) examine the intraday return/order imbalance relationship to investigate the convergence process toward efficiency of daily top gainers in the U.S. market. These studies are carried out in dealer market, where market makers accommodate buying and selling pressures from the general public.

Recently many researchers have extended the study of order imbalances from dealer market to pure order-driven market to investigate whether there exists any difference of the conclusion in these two markets. Lee et al. (2004) study the relationship between order imbalances and market efficiency of different types of investors in TWSE. Huang and Chou (2007) compare the impacts of order imbalance on market performance at the two Taiwan stock index future markets, the TAIFEX order-driven market and the SGX-DT quote-driven market. Li et al. (2010) construct a new order imbalance measure, limit order imbalance, and find the conventional “market order imbalance” together with their new “limit order imbalance” can explain more than 90% of intraday returns of the Nikkei 225 Futures in Japan.

Shenoy and Zhang (2007) use the Chinese stock market data from July to December 2004 and find a strong contemporaneous relation between daily order imbalances and returns of individual stocks in the Chinese stock markets of Shanghai and Shenzhen, but they do not find evidence that order imbalances predict subsequent returns. However, Zhou and Wang (2009) find that the order imbalance has a power of explanation and prediction for individual stock returns in the order-driven Hong Kong stock market. Seasholes and Liu (2011) study the trading of Chinese (mainland)/ Hong Kong dual-listed shares, and show that the difference in order

[*] We thank the editor and referees for helpful comments, and we are also grateful for the research support provided by the Humanities & Social Science Fund of the Chinese Ministry of Education (Grant No.11YJC790014).

imbalances across these two exchanges is economically and statistically related to changes in the AH Premium Index.

Although volatility has always been the research interest of many scholars (e.g. Horng and Chyan (2009), Li and Xiao (2011)), little has been done on the relationship between order imbalance and individual stock volatility. We would like to address this problem using Chinese high frequency data in this paper. In particular, we investigate the relationship between daily order imbalances and individual stock returns and volatility using the data of SSE 180 index stocks in 2007. We find that daily order imbalances are positively auto-correlated, and contemporaneous order imbalance exerts an extremely significant impact on individual stock returns and volatility, but lagged order imbalance has no power of prediction for individual stock returns and volatility.

The remainder of this paper is organized as follows. Section 2 proposes some hypothesis to be tested in this paper. Section 3 describes the data. Section 4 discusses the relationship between order imbalance and individual stock returns. Section 5 discusses the relationship between order imbalance and individual stock volatility. Section 6 concludes.

2. Hypothesis

For the interests of this study, we propose following hypothesis:

Hypothesis 1: Order imbalances are positively auto-correlated. This arises from the splitting of large orders over time to reduce price impact by institutional investors and the herding by retail investors.

Hypothesis 2: Individual stock returns are strongly affected by contemporaneous order imbalances. Order imbalance represents the net transaction demand of investors in dealer markets, so it's obvious that positive order imbalance (i.e. excess buy) would push the stock price up and vice versa. In order-driven market, although there are no designated market makers, the limit orders submitted by investors play the role of providing liquidity as market makers do, and can be taken as implicit market makers in the market.

Hypothesis 3: Lagged order imbalance has a negative impact on stock returns when accompanied by its contemporaneous counterpart. The price response to the contemporaneous imbalance has two components (Chordia and Subrahmanyam, 2004), a large independent premium termed as the innovation component, and a smaller auto-correlated portion termed as history-dependent component. Conditioning only on the total contemporaneous imbalance assigns the same weight to both of these two parts. The negative coefficient on lagged imbalances arises because of this ''over-weighting'' of history-dependent trades in the current imbalance.

Hypothesis 4: Order imbalance has a positive impact on contemporaneous volatility. Large order imbalance, no matter excessive buy or excessive sell, exerts a big impact on stock price changes. The absolute value of order imbalance should have a positive impact on contemporaneous volatility.

3. Data

We use the stocks in the SSE 180 index and the sample period covers the whole year of 2007. To be included in our sample, the stock has to be listed all through the year. We have 152 stocks after this screening. All the data used in this study are obtained from WIND database.

3.1. Variables

The computations of the variables used in this study are as follows:

1. Measures of order imbalance

We use the tick data to compute the daily order imbalance in shares for stock *i* on day *t* as OIB_SH_{it}, which is the buyer-initiated shares less the seller-initiated shares for stock *i* on day *t*. Similarly, we compute the order imbalance in RMB volume as OIB_DOL_{it}. In order to eliminate the impact of trading volume, we also compute the scaled order imbalance OIB_s_{it} as OIB_SH_{it} scaled by total trading volume of stock *i* on day *t* (SH_{it}).

2. Measure of liquidity

We construct the Amihud (2002) illiquidity measure ($Illiquid_{it}$) to reflect the liquidity of the stock indirectly. The Amihud illiquidity measure is calculated by:

$$Illiquid_{it} = \frac{|R_{it}|}{DOL_{it}} = \frac{|\ln(P_{it}) - \ln(P_{it-1})|}{DOL_{it}},$$

where R_{it} is the return of individual stock *i* on day *t*, P_{it} and P_{it-1} are close prices of stock *i* on day *t* and day *t-1* respectively, DOL_{it} is the trading volume of stock *i* in RMB on day *t*.

3. Measure of volatility

Following Chordia et al. (2002), we use the absolute value of daily returns ($|R_{it}|$) as the measure of stock volatility.

3.2. Descriptive statistics and correlations

Table 1 reports the descriptive statistics of these variables. We calculate the time series average of variables for 152 stocks and Table 1 reports their cross sectional mean and standard deviation. The mean of OIB_SH, OIB_DOL and R are all positive. The direction of net market orders is 'buy', and the direction of net limit orders is 'sell'. Since the stock return is positive in our sample period, this suggests that limit orders have typically been on the wrong side of trades during this period. The scaled order imbalance OIB_s has small but negative mean, indicating that there are more days with large selling pressure than with large buying pressure.

Table 1. Descriptive statistics

	Mean	**Standard deviation**
OIB_SH (10^5)	8.6462	33.0903
OIB_DOL (10^6)	9.7446	46.7940
OIB_s	-0.0027	0.1224
SH (10^7)	2.7507	1.6140
DOL (10^8)	3.7353	2.3166
R	0.0043	0.0387
|R|	0.0299	0.0249
Illiquid (10^{-10})	2.7604	9.0708

Note: the number in parentheses is the order of magnitude for each variable.

We calculate the time-series correlations among these variables for each stock. Table 2 reports their cross sectional means. The two unscaled order imbalance measures, OIB_SH and OIB_DOL, are strongly positively correlated (the correlation coefficient as high as 0.9604), and the correlations between unscaled (OIB_SH and OIB_DOL) and scaled (OIB_s) order imbalance measures are also high (0.8212 and 0.8075 respectively). The correlations between three order imbalance measure (OIB_SH, OIB_DOL, and OIB_s) and stock returns are 0.4868, 0.4702 and 0.5000 respectively. These are higher than the correlation between trading volume and stock returns. Trading activity and stock returns are more related through order imbalances than total trading volume.

Table 2. Correlations

	OIB_DOL	**OIB_s**	**SH**	**DOL**	**R**	**|R|**	**Illiquid**
OIB_SH	0.9604^a	0.8212^a	0.2961^a	0.2792^a	0.4868^a	0.0988^a	-0.0807^a
OIB_DOL		0.8075^a	0.2921^a	0.3069^a	0.4702^a	0.1022^a	-0.0852^a
OIB_s			0.2343^a	0.2209^a	0.5000^a	0.0454^a	-0.1591^a
SH				0.8606^a	0.2163^a	0.3294^a	-0.2589^a
DOL					0.1969^a	0.3087^a	-0.3202^a
R						0.0246^b	-0.1204^a
|R|							0.5807^a

Note: superscript [a], [b] denote significant at the 1%, and 5% level, respectively.

Table 3 reports the cross-sectional average of the autocorrelations of order imbalance measures in each stock. Consistent with hypothesis 1, all three order imbalance measures (OIB_SH, OIB_DOL and OIB_s) have positive autocorrelations up to at least five daily lags except the second lag of OIB_SH. Thus, there is strong evidence that a significant number of trades in one direction is followed by further trading activity in the same direction.

Table 3. Autocorrelations

Lag (days)	OIB_SH	OIB_DOL	OIB_s
1	0.0210[a]	0.0342[a]	0.0493[a]
2	-0.0019	0.0038	0.0124[c]
3	0.0173[a]	0.0138[b]	0.0348[a]
4	0.0243[a]	0.0296[a]	0.0492[a]
5	0.0087	0.0160[b]	0.0027

Note: superscript [a], [b], [c] denote significant at the 1%, 5%, and 10% level, respectively.

4. Order imbalance and individual stock returns

In this section, we follow Chordia and Subrahmanyam (2004) and run the time-series regressions to explore the relationship between daily returns and order imbalance, i.e.,

$$R_{it} - R_{mt} = a_i + b_{i1}OIB_{i,t} + b_{i2}OIB_{i,t-1} + b_{i3}OIB_{i,t-2} + b_{i4}OIB_{i,t-3} + b_{i5}OIB_{i,t-4} + e_i\,, \tag{1}$$

where R_{it} denotes the return of individual stock i on day t. R_{mt} denotes the market return on day t, which is measured by the return of SSE 180 index on day t. $OIB_{i,t}$ denotes the order imbalance measures for stock i on day t (either OIB_SH or OIB_s)[1].

Table 4 reports the mean coefficients from the time-series regression (1) for each stock. 'Significant' denotes significant at least at the 10% level. Panel A of Table 4 reports the empirical results for OIB_SH, and Panel B reports the results for OIB_s. The results in Panel A indicate the average coefficient of contemporaneous order imbalance is 8.6294, and about 97.37% of the coefficients are positive, with about 94.08% being positive and significant. Further, the average coefficients on lagged order imbalances are all negative. For example, the average coefficient of one day lagged order imbalance is -0.2655, and about 69.74% of the coefficients are negative, with about 17.76% being negative and significant. Panel B of Table 4 reports similar results. Table 4 shows that the contemporaneous order imbalance exerts a significant positive impact on individual stock returns, and lagged order imbalance exerts a negative effect on the current day's stock return after controlling for the contemporaneous order imbalance. This is consistent with the hypothesis 2 and hypothesis 3.

In order to investigate whether predictability exists without contemporaneous order imbalance information, we exclude contemporaneous order imbalance from the time-series regression for each stock, i.e,

$$R_{it} - R_{mt} = a_i + b_{i1}OIB_{i,t-1} + b_{i2}OIB_{i,t-2} + b_{i3}OIB_{i,t-3} + b_{i4}OIB_{i,t-4} + b_{i5}OIB_{i,t-5} + e_i\,. \tag{2}$$

Table 5 reports the mean coefficients. The results show that most of the coefficients of lagged order imbalances are insignificant. Lagged order imbalances alone have no power of prediction for stock returns. This is consistent with Shenoy and Zhang (2007) but different from Chordia and Subrahmanyam (2004).

[1] The results of order imbalance measure OIB_DOL are quite similar and available upon request.

Table 4. Order imbalance and individual stock returns

Variable	Average coefficient	Average p-value	Percent positive (%)	Percent positive and significant (%)	Percent negative and significant (%)
Panel A:					
OIB_SH_{it}	8.6294	0.02	97.37	94.08	0.66
OIB_SH_{it-1}	-0.2655	0.41	30.26	5.26	17.76
OIB_SH_{it-2}	-0.8133	0.39	19.74	1.32	21.05
OIB_SH_{it-3}	-0.6118	0.48	28.29	1.97	9.21
OIB_SH_{it-4}	-0.2416	0.46	42.11	3.29	11.18
Panel B:					
OIB_s_{it}	0.1014	0.02	98.03	94.74	0.66
OIB_s_{it-1}	-0.0101	0.41	30.26	2.63	15.13
OIB_s_{it-2}	-0.0123	0.43	19.74	0.66	16.45
OIB_s_{it-3}	-0.0050	0.48	35.53	3.29	13.16
OIB_s_{it-4}	-0.0037	0.47	40.13	3.95	8.55

Note: the order of magnitude of OIB_SH is 10^{-9}.

Table 5. Order imbalance and future individual stock returns

Variable	Average coefficient	Average p-value	Percent positive (%)	Percent positive and significant (%)	Percent negative and significant (%)
Panel A:					
OIB_SH_{it-1}	-1.9604	0.43	34.87	5.92	13.16
OIB_SH_{it-2}	-9.9369	0.40	20.39	0.66	21.71
OIB_SH_{it-3}	-5.8752	0.48	38.16	3.29	9.87
OIB_SH_{it-4}	-0.8209	0.46	50.00	2.63	9.87
OIB_SH_{it-5}	-5.8122	0.49	39.47	2.63	11.84
Panel B:					
OIB_s_{it-1}	-0.0083	0.43	36.18	2.63	12.50
OIB_s_{it-2}	-0.0138	0.40	19.08	1.97	17.11
OIB_s_{it-3}	-0.0019	0.48	44.08	3.29	7.89
OIB_s_{it-4}	0.0015	0.46	53.29	5.92	2.63
OIB_s_{it-5}	-0.0027	0.51	45.39	1.32	5.26

Note: the order of magnitude of OIB_SH is 10^{-10}.

5. Order imbalance and individual stock volatility

We then run the time-series regressions to explore the relationship between stock volatility and order imbalance. We introduce liquidity measure to control any liquidity effect on volatility, and the lagged absolute return to account for the well-documented persistence in volatility. The time series regressions are [1]

$$|R_{it}| = a_i + b_{i1}|OIB_{i,t}| + b_{i2}DOL_{it} + b_{i3}Illiquid_{it} + b_{i4}|R_{it-1}| + e_i \quad (3)$$

$$|R_{it}| = a_i + b_{i1}|OIB_{i,t-1}| + b_{i2}DOL_{it-1} + b_{i3}Illiquid_{it-1} + b_{i4}|R_{it-1}| + e_i \quad (4)$$

[1] To check the robustness of the results, we also use another volatility measure, HL, to run the regressions (3) and (4). The volatility measure HL is defined as (PH-PL)/((PH+PL)/2), where PH and PL are the highest and lowest daily price of individual stock, respectively. The results are weaker but still robust, and available upon request.

Table 6 reports the mean coefficients of the time-series regression (3) for each stock. 'Significant' denotes significant at least at the 10% level. Panel A of Table 6 reports the empirical results for OIB_SH, and Panel B reports the results for OIB_s. The results in Panel A indicate the average coefficient of absolute contemporaneous order imbalance is 4.4541, and about 96.71% of the coefficients are positive, with about 84.21% being positive and significant. Panel B shows similar results. Order imbalance has a significant positive impact on contemporaneous stock volatility, which supports the hypothesis 4 that both excessive buy and excessive sell lead to an increase of contemporaneous volatility.

Table 7 reports the mean coefficients of the time-series regression (4) for each stock. The results show that most of the coefficients of lagged order imbalance are insignificant. Lagged order imbalance has no power of prediction for stock volatility.

Table 6. Order imbalance and individual stock volatility

Variable	Average coefficient	Average p-value	Percent positive (%)	Percent positive and significant (%)	Percent negative and significant (%)
Panel A:					
$\lvert OIB\_SH_{it} \rvert$ (10^{-9})	4.4541	0.07	96.71	84.21	0.66
DOL_{it} (10^{-11})	8.2516	0.01	98.68	98.03	0.66
$Illiquid_{it}$ (10^{8})	2.1295	0.00	100	100	0
$\lvert R_{it-1} \rvert$	0.0068	0.39	51.32	14.47	12.5
Panel B:					
$\lvert OIB\_s_{it} \rvert$	0.0204	0.25	79.61	44.74	3.95
DOL_{it} (10^{-10})	1.0206	0.00	100	100	0
$Illiquid_{it}$ (10^{8})	2.1662	0.03	99.34	95.39	0
$\lvert R_{it-1} \rvert$	0.0003	0.39	48.68	13.16	17.11

Note: the number in parentheses is the order of magnitude for each variable.

Table 7. Order imbalance and future individual stock volatility

Variable	Average coefficient	Average p-value	Percent positive (%)	Percent positive and significant (%)	Percent negative and significant (%)
Panel A:					
$\lvert OIB\_SH_{it-1} \rvert$ (10^{-11})	-7.7648	0.47	43.43	8.55	10.53
DOL_{it-1} (10^{-11})	1.3402	0.40	74.34	25.66	1.32
$Illiquid_{it-1}$ (10^{7})	1.7422	0.43	50.66	10.53	6.58
$\lvert R_{it-1} \rvert$	0.0490	0.34	59.87	23.03	5.92
Panel B:					
$\lvert OIB\_s_{it-1} \rvert$	-0.0051	0.48	45.39	4.61	7.24
DOL_{it-1} (10^{-11})	1.2291	0.39	78.29	22.37	2.63
$Illiquid_{it-1}$ (10^{7})	1.8209	0.44	46.71	9.87	7.24
$\lvert R_{it-1} \rvert$	0.0474	0.34	62.50	25.00	7.24

Note: the number in parentheses is the order of magnitude for each variable.

6. Conclusions

This paper studies the impact of order imbalance on individual stock returns and individual stock volatility in the order-driven Chinese stock market. Our empirical results find that there exists a positive autocorrelation in the daily order imbalance which might be due to investors' order splitting or herding behavior. Order imbalance could explain contemporaneous returns and volatility. One possible explanation is that the imbalance in order-driven market signals the excessive interest of market order submitters who are taken as more aggressive than limit order submitters and usually have more private information. We also find that when accompanied by its contemporaneous counterpart, lagged order imbalance has a negative impact on stock returns because of the ‘‘over-weighting’’ of history-dependent trades in the current imbalance. However, the lagged order imbalance has no power of prediction for future returns and volatility when not accompanied by its contemporaneous counterpart. Since the short-horizon return predictability from order flows is an inverse indicator of market efficiency (Chordia et al., 2008), our results may show market efficiency in Chinese stock market at least in daily frequency.

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