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Full Length Research Paper

Dynamic intraday relations between order imbalance, volatility and return of jump losers

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This study adopted intraday return instead of daily return used by previous researches to examine the effect of order imbalance not only on the individual stock return but also volatility among jump losers. The study also built up order imbalance-based trading strategies to earn abnormal return. A contemporaneous order imbalance-return relation was examined by GARCH (1,1) model and time-series regression model. The data presented significantly positive relation in both models as previous studies on daily return. The study focused on the lagged effect of imbalance on return and found that such relation was negatively significant, while contemporaneous imbalance had positive significant impact on return. The study examined the volatility-order imbalance relationship by a time-varying GARCH (1,1) model. The positive relation of volatility and order imbalance was consistent with the ex-ante expectation that larger imbalance made return more volatile. The study developed two order imbalance-based trading strategies based on different definitions of price: trading price and bid-ask. Due to the characteristics of our jump losers, we used short selling strategy. The results showed the huge profitability of order imbalance strategies when we traded on extreme volume.

Key words: Order imbalance, information asymmetry, volatility, causal relationship.

INTRODUCTION

Recently, researches have been devoted to exploring the relation between stock price movements and trading activity, where the latter is usually represented by trading volume. According to Karpoff (1987) and his exploration on previous empirical researches, trading volume not only had positive correlation with stock price, but also with stock volatility. Later on, a number of researches also prove this relationship (Gallant et al., 1992; Lo and Wang, 2000).

Trading volume, however, can be high either due to buyer-initiated or seller-initiated trade. The different distributions between buyer and sellers have different implications. In one hand, order imbalance could signal private information which can reduce liquidity temporarily, as suggested by Kyle (1985) theory of price formation. The author related price change to net order flow and provides the idea of information asymmetry for the effect on stock return. On the other hand, a high absolute order imbalance exacerbates the inventory problem faced by the market makers, who can be expected to respond by changing bid-ask spreads and revising price quotation. Thus, investigating directly on order imbalance itself is more appropriate than through trading volume caused by order imbalance (Chan and Fong, 2000; Chordia et al., 2002).

Based on Llorente et al. (2002), there are two motives of trade: hedging for risk sharing and speculate on the private information. Speculative trades generate positively auto-correlated return because of the momentum effect. This is why we focus on speculative jump losers to observe the return-order imbalance relationship and to build up order imbalance-based strategies to earn abnormal return.

Following the method of Lee and Ready (1991), if a transaction occurs above (below) the prevailing quote mid-point, it is regarded as a buyer (seller)-initiated trade. Then we start our research. Firstly, the relation between

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intraday contemporaneous order imbalance and intraday stock returns is examined by GARCH (1,1) model and time-series regression model, where the latter is addressed by Chordia and Subrahmanyam (2004). Secondly, the revised time-series regression model is used to verify the predictability in lagged order imbalance to future return.

Thirdly, after examining the return-imbalance relationship, the study investigates where higher order imbalance is associated with volatile stock return. Fourthly, as Llorente et al. (2002), the study considers market capitalization an important factor of speculative trading.

Fifthly, given the evidence of the strong relationship between return and order imbalance, we build up order imbalance-based trading strategies. Because of the characteristics of our samples, jump losers, we adopt the short selling strategy. That means we short sell a stock when observed negative order imbalance. We hold our short sell position until the order imbalance turn to be a positive sign while we buy back to cover the short position. There are two price definitions: trading price and bid-ask.

In order to explore the story behind the successful trading strategies, the study examines nested causality relations between order imbalance and return. According to Chen and Wu (1999), the study defines four groups of dynamic relationship, namely independency ($\wedge$), the contemporaneous relationship ($\leftrightarrow$), unidirectional relationship ($\Rightarrow$ or $\Leftarrow$) and feedback relationship (< = >). To determine a specific causal relationship, the study uses a systematic multiple hypotheses testing method. Unlike the traditional pair-wise hypothesis testing, this testing method avoids the potential bias induced by restricting the causal relationship to a single alternative hypothesis.

DATA AND METHODOLOGY

The study collects intraday transaction data from the Center for Research in Security Prices (CRSP) and NYSE Trades and Automated Quotations (TAQ) database. The sample period is from January 1, 2005 to December 31, 2005 with 53 sample stocks.

Qualified stocks are defined depending on the following criteria: i) individual speculative jump stocks with return lower than -35% on the transaction day are sampled; ii) the jump losers, whose trading volume range between 1 million and 4 million shares are chosen. Order imbalance is used as proxy to the extent of information asymmetry while analyzing its effects on individual stock return. Accordingly, the trading volume should be large enough for observing information asymmetry. Furthermore, low liquidity thin stocks are too risky for the speculators to liquidate; iii) the study eliminates samples with closing price less than \$ 2. It can avoid the influence of unduly low-priced stocks; iv) the study eliminates samples with number of trade more than 10 thousands.

Then, the study uses the algorithm of Lee and Ready (1991). If a transaction occurs above (below) the prevailing quote mid-point, it is regarded as a buyer (seller)-initiated trade. If a transaction occurs exactly at the mid-point, it is signed using the previous transaction price according to the tick test (buys if the sign of the last non-zero price change is positive and vice versa). The daily return of the jump losers in our sample are all below – 35%. The average intraday return is pretty close to zero. The negative sign of the average intraday return, -0.0194%, comes from the characteristics of jump losers in the sample. The average of sum and mean of each sample's order imbalance are -267,021 and -64, respectively.

Besides, there are more seller-initiated orders than buyer-initiated orders. All stated results are consistent with the characteristics of our samples, the jump losers.

The average market capital is 269.19 million with the standard deviation of 405.53 million. Although the firm size is quite diverse with range of about 2.5 billion, almost 77.36% of the samples have the firm size below 300 million. These results mean that the majority of jump losers are small caps.

There are five procedures in the research. First of all, the study uses the GARCH (1,1) model to investigate the intraday time varying return-order imbalance relation. The study expected a positive return-order imbalance relation.

Secondly, it uses two time-series regression model to check whether the conditional contemporaneous and unconditional lagged order imbalances can explain the stock return or not. Thirdly, it focuses on the relationship between volatility and order imbalance through GARCH (1, 1) model.

The study expected a positive volatility-order imbalance relation. Larger volatility is associated with larger buyer (seller) initiated order. Fourthly, the study tries to figure out whether the small firm effect does exist based on Llorente et al. (2002). Fifthly, it addresses two order imbalance-based strategies and tests the profitability under different scenario.

At last, in order to explore the story behind the successful order imbalance based strategy, the study uses a nested hypotheses testing method to determine the specific causal relationship between return and order imbalance.

A GARCH (1,1) model is employed to capture the time varying property of stock return. A typical GARCH (1,1) model looks like:

$$\begin{aligned} R_t &= \alpha_0 + \alpha_1 * OI_t + \varepsilon_t \\ \varepsilon_t | \Omega_{t-1} &\sim N(0, h_t) \\ h_t &= \beta_0 + \beta_1 * h_{t-1} + \beta_2 * \varepsilon_{t-1}^2 \end{aligned} \quad (1)$$

where, R_t is the return in period t, defined as $\ln\left(\frac{P_t}{P_{t-1}}\right)$; α_1 is the coefficient describing the impact of "order imbalance" on stock returns; OI_t is the explanatory variable and means order imbalance. If it is a buyer-initiated order, it is the positive sign, and vice versa; h_t is the conditional variance in period t; ε_t is the residual term of the stock return, and is conditional on an information set in period t-1, which follows normal distribution; Ω_{t-1} is the information set in period t-1.

As Barclay and Warner (1993) proposed, empirical research shows that volatility of price is caused primarily by private information revealed through trading rather than public information released. We are interested in the relation between order imbalance and volatility. Therefore, the study adjusts the GARCH (1,1) model as:

$$\begin{aligned} R_t &= \alpha_0 + \varepsilon_t \\ \varepsilon_t | \Omega_{t-1} &\sim N(0, h_t) \\ h_t &= \beta_0 + \beta_1 * h_{t-1} + \beta_2 * \varepsilon_{t-1}^2 + C_1 * OI_t \end{aligned} \quad (2)$$

All the parameters have the same meaning as the GARCH model mentioned before. The only difference is derived from the components of h_t, the conditional variance in period t. OI_t is added as the independent variable to examine the explanatory power of the volatility of return. Based on the influence the order imbalance has to the intraday return, we would expect positive C_1 in the results.

Firm size is usually considered as a proxy of information asymmetry as Lo and MacKinlay (1990), and Llorente et al. (2002) found that smaller firms have a higher degree of information asymmetry or higher adverse selection costs. Because of the lower information transparency, the price of small firm may be more volatile than that of big firm. Such situations make speculators have the chance to yield abnormal profits due to information trading.

Given the evidence of the strong relationship between return and order imbalance from the previous model, the study tests the profitability of order imbalance-based trading strategies. The study develops two order imbalance based trading strategies.

Strategy A: Buy at the trading price when OI is positive, and sell at the trading price when OI is negative

Due to the downward tendency of jump losers, the study considers a short sell strategy. When the first negative order imbalance is observed, we short sell a share at the trading price associated with this negative order imbalance. Then, we hold our short sell position until the order imbalance turns positive and buy back at the trading price associated with this positive order imbalance to square the short position.

We repeat this trading rule during the transaction day. In order to get rid of noised trades, we truncate the distribution of order imbalance under different scenario, such as 90th and 99thpercentile of imbalances. Furthermore, since the frequency of transactions of some stocks is still too high to execute practically in 99th percentile category, we heighten the critical imbalance to reduce the frequency down under five times.

Strategy B: Buy ask price when OI is positive, and sell bid when OI is negative

However, in real trading, instead of trading at the market traded price, we can only trade on the bid-ask quotation of market makers. Hence, we use another more conservative strategy, Strategy B. The trading rules are similar to Strategy A. The only difference is the buy and sell price of our trade. Here, we short sell a share at the bid (the bid quote matched to this negative order imbalance). Additionally, we buy back at ask (ask quote matched to the positive order imbalance) to cover the short position. Instead trading at the best execution price as Strategy A, we sell stock at a lower price and buy back at a higher one in Strategy B. We expected a lower return in this strategy.

In order to explore the dynamic return-order imbalance relation, we employ a nested causality approach. 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.

Definition 1: Independency, $x_1 \wedge x_2$

x_1 and x_2 are independent if:

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{2(T+1)}}) \quad (3)$$

and

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) = Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) = Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{1(T+1)}}) \quad (4)$$

Definition 2: Contemporaneous relationship, $x_1 <-> x_2$

x_1 and x_2 are contemporaneously related if:

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) \quad (5)$$

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) > Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{2(T+1)}}) \quad (6)$$

and

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) = Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) \quad (7)$$

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) > Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{1(T+1)}}) \quad (8)$$

Definition 3: Unidirectional relationship, $x_1 => x_2$

There is a unidirectional relationship from x_1 to x_2 if:

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) \quad (9)$$

and

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) > Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) \quad (10)$$

Table 1. Hypotheses on the dynamic relationship of a bivariate system.

Hypotheses	The VAR test
$H_1 : x_1 \wedge x_2$	$\varphi_{12}(L) = \varphi_{21}(L) = 0$, and $\sigma_{12} = \sigma_{21} = 0$
$H_2 : x_1 <-> x_2$	$\varphi_{12}(L) = \varphi_{21}(L) = 0$
$H_3 : x_1 \neq> x_2$	$\varphi_{21}(L) = 0$
$H_3^* : x_2 \neq> x_1$	$\varphi_{12}(L) = 0$
$H_4 : x_1 <=> x_2$	$\varphi_{12}(L) * \varphi_{21}(L) \neq 0$
$H_5 : x_1 \neq>> x_2$	$\varphi_{21}(L) = 0$, and $\sigma_{12} = \sigma_{21} = 0$
$H_6 : x_2 \neq>> x_1$	$\varphi_{12}(L) = 0$, and $\sigma_{12} = \sigma_{21} = 0$
$H_7 : x_1 <<=>> x_2$	$\varphi_{12}(L) * \varphi_{21}(L) \neq 0$, and $\sigma_{12} = \sigma_{21} = 0$

The bivariate VAR model: $\begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$ where x_{1t} and x_{2t} are mean adjusted variables. The first and second moments of the error structure, $\underset{\sim}{\varepsilon_t} = (\varepsilon_{1t}, \varepsilon_{2t})'$, are that $E(\underset{\sim}{\varepsilon_t}) = 0$, and $E(\underset{\sim}{\varepsilon_t}\, \underset{\sim}{\varepsilon_{t+k}}) = 0$ for $k \neq 0$ and $E(\underset{\sim}{\varepsilon_t}\, \underset{\sim}{\varepsilon_{t+k}}) = \Sigma$ for $k=0$, where $\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$

The causal relationship are defined as follows: $\wedge$ is independency; $<->$ is contemporaneous relationship; $\neq>$ is negation of a unidirectional relationship; $<=>$ is feedback relationship; $\neq>>$ is negation of a strong unidirectional relationship where $\sigma_{12} = \sigma_{21} = 0$; and $<<=>>$ is a strong feedback relationship where $\sigma_{12} = \sigma_{21} = 0$.

Definition 4: Feedback relationship, $x_1 <=> x_2$

There is a feedback relationship between x_1 and x_2 if

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) > Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) \qquad (11)$$

and

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) > Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) \qquad (12)$$

To explore the dynamic relationship of a bi-variate system, we form the five statistical hypotheses in the Table 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.

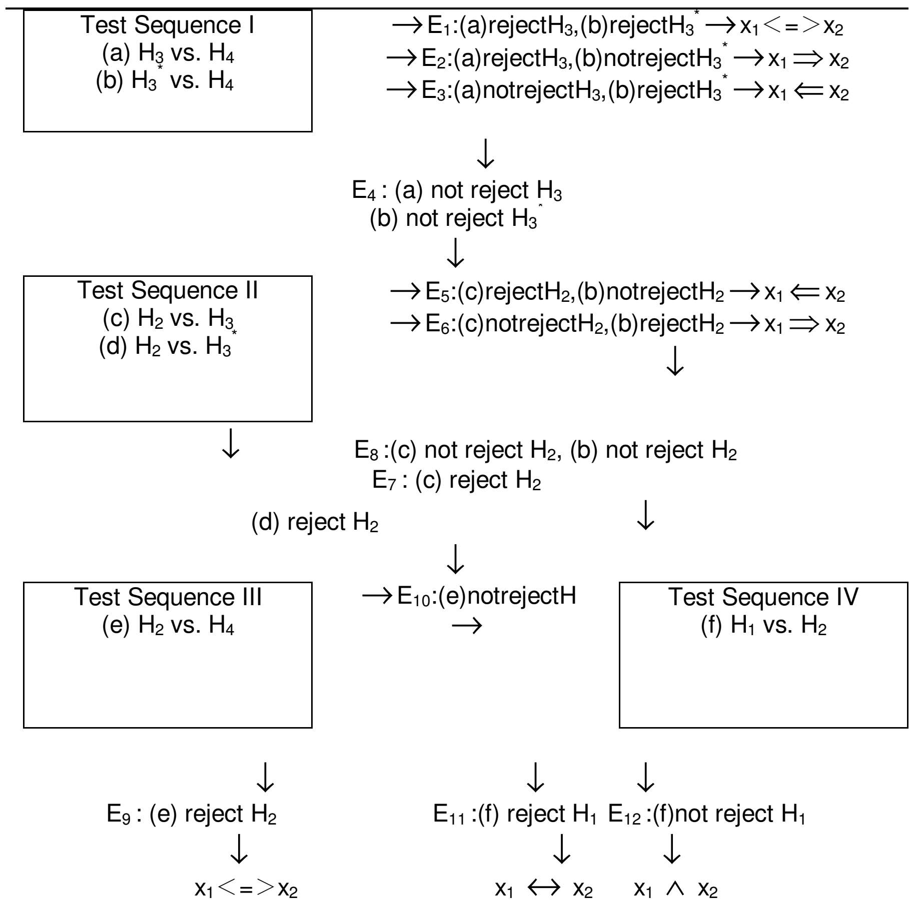
To determine a specific causal relationship, the study uses a systematic multiple hypotheses testing method. Unlike the traditional pair-wise hypothesis testing, this testing method avoids the potential bias induced by restricting the causal relationship to a single alternative hypothesis.

To implement this method, the study employs results of several pair-wise hypothesis tests. For instance, in order to conclude that $x_1 => x_2$, we need to establish that $x_1 < \neq x_2$ and to reject that $x_1 \neq > x_2$. To conclude that $x_1 <-> x_2$, we need to establish that $x_1 < \neq x_2$ as well as $x_1 \neq > x_2$ and also to reject $x_1 \wedge x_2$. 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.

The 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, the study intends 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 Table 2. The inference procedure starts from executing tests (a) and (b), which result in one of the four possible outcomes, E_1, or E_4. The three outcomes, E_1, E_2, and E_3, that lead to the conclusions of $x_1 <=> x_2$, $x_1 => x_2$, *and* $x_1 <= x_2$, respectively, will stop the procedure at the end of the first step. Nonetheless, when outcome E_4 is realized, tests (c) and (d) will be implemented. There again one of the four possible outcomes, E_5 , . . . , or E_8 , will be realized. The realization of outcomes E_5 and E_6, which respectively indicates $x_1 <= x_2$, and $x_1 => x_2$, will stop the procedure at the end of Step 2. On the other hand, the realization of outcome E_7 would lead to test (e) in Step 3, which has the consequence of either outcome E_9 or outcome E_{10}. Outcome E_9 implies $x_1 <=> x_2$ and the procedure will stop. Either outcome E_8 from Step 2 or outcome E_{10} from Step 3 will lead to test (f) in Step4. This last step may generate two possible results, E_{11} and E_{12}, which imply $x_1 <-> x_2$ and $x_1 \wedge x_2$, respectively.

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



Five groups of dynamic relationship are identified: independency ($\wedge$), the contemporaneous relationship ($\leftrightarrow$), unidirectional relationship ($\Rightarrow$ or $\Leftarrow$) and feedback relationship ($<=>$). 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. In implementing this method, we need to employ results of several pairwise hypothesis tests. For instance, in order to conclude that $x_1 => x_2$, we need to establish that $x_1 <\neq x_2$ and to reject that $x_1 \neq> x_2$. To conclude that $x_1 <-> x_2$, we need to establish that $x_1 <\neq x_2$ as well as $x_1 \neq> x_2$ and also to reject $x_1 \wedge x_2$. In other words, it is necessary to examine all five hypotheses in a systematic way before a conclusion of dynamic relationship can be drawn.

EMPIRICAL RESULTS

Dynamic return-order imbalance relation

This study takes order imbalance as the proxy of information asymmetry and explores the relation between intraday return and levels of order imbalance using GARCH (1,1) model. In Table 3, under 95% confidence levels, the percentage of positive significant α_1's is 81.13%. Positive α_1 means that a big buyer-initiated order is associated with a higher return. In other words, the high percentage of positive α_1 indicates that the order imbalance has a positive influence on return. This evidence is consistent with previous studies such as Llorente et al. (2002), even though bid-ask ratio is used as proxy to information asymmetry in their research.

Conditional contemporaneous and unconditional lead-lag return-order imbalance relations

Here, we reexamine the relation between intraday returns and conditional contemporaneous order imbalance by the times-series regression model suggested by Chordia and Subrahmanyam (2004).

Table 3. Return-order imbalance relation in a GARCH (1,1) Model.

	Percent positive (%)	Percent positive and significant (%)	Percent negative and significant (%)
α_1	90.56	81.13	5.66
β_1	100.00	100.00	0.00

"Significant" denotes significant at the 5% level.

$$R_t = \alpha_0 + \alpha_1 * OI_t + \varepsilon_t$$

$$\varepsilon_t \big| \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 * h_{t-1} + \beta_2 * \varepsilon_{t-1}^2$$

R_t: the return on time t, defined as $\ln\left(\frac{P_t}{P_{t-1}}\right)$

OI_t: the order imbalance on time t. If it is a buyer-initiated order, it is the positive sign, and vice versa
ε_t: the residual term of the stock return, and is conditional on an information set of time t-1
h_t: the conditional variance on time t.

Table 4. Conditional contemporaneous relations between return and lag order imbalances.

	Average coefficient	Percent positive (%)	Percent positive and significant (%)	Percent negative and significant (%)
γ_0	7.7531E-07 (9.93)	100	100	0.00
γ_1	-6.5994E-07 (-7.41)	3.77	0.00	94.34
γ_2	7.6291E-09 (-0.39)	41.51	3.77	15.09
γ_3	4.6827E-08 (0.35)	60.38	11.32	5.66
γ_4	4.6022E-08 (0.04)	60.38	3.77	5.66

"Significant" denotes significant at the 5% level.

$$R_{it} = \alpha_i + \gamma_{i0} OI_{i,t} + \gamma_{i1} OI_{i,t-1} + \gamma_{i2} OI_{i,t-2} + \gamma_{i3} OI_{i,t-3} + \gamma_{i4} OI_{i,4} + e_i$$

R_{it} : the return of sample stock i on time t, defined as $\ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$.

$OI_{i,t-j}$, j= 0, 1,…, 4: the order imbalance of sample stock i on time t, t-1,…, t-4. If it is a buyer-initiated order, it is the positive sign, and vice versa.

e_i : the residual term of each equation.

Conditional contemporaneous return-order imbalance relation

Table 4 exhibits the percentage of significances of the five order imbalance coefficients under 95 percent confidence level. All of the contemporaneous coefficients, γ_0, are positive and significant under 5% confidence level. Moreover, 96.23% of the coefficients of lag-one imbalances are negative, with 94.34% significantly negative under 95% confidence level. Therefore, no matter under GARCH or time-series regression model, the contemporaneous relation between order imbalance and return is consistent with both inventory and asymmetric information effects of price formation. Besides γ_0 and γ_1, the study turns to focus on the influence of order imbalance of other periods. It finds that the percentage of negative significance of γ_2, γ_3 and γ_4 is quite low, even close to zero. This result is not consistent with Chordia and Subrahmanyam (2004). They observed that the effect of auto correlated imbalances on return is quite long-lived. We believe that market efficiency tells the difference, especially in the intraday return.

Unconditional lead-lag return-order imbalance relation

The study tries to figure out whether the lagged order

Table 5. Unconditional lead-lag relations between return and lag order imbalances.

	Average coefficient	Percent positive (%)	Percent positive and significant (%)	Percent negative and significant (%)
δ_1	-5.6761E-07 (-6.44)	5.66	1.89	83.02
δ_2	5.4451E-08(-0.08)	52.83	7.55	15.09
δ_3	5.4326E-08 (0.52)	64.15	13.21	3.77
δ_4	5.1195E-08 (0.19)	60.38	0.00	3.77
δ_5	5.4057E-08 (0.39)	56.60	13.21	1.89

"Significant" denotes significant at the 5% level.

$$R_{it} = \alpha_i + \delta_{i1}OI_{i,t-1} + \delta_{i2}OI_{i,t-2} + \delta_{i3}OI_{i,t-3} + \delta_{i4}OI_{i,t-4} + \delta_{i5}OI_{i,5} + e_i$$

R_{it} : the return of sample stock i on time t, defined as $\ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$.

$OI_{i,t-j}$, j= 1, 2,…, 5: the order imbalance of sample stock i on time t-1, t-2,…, t-5. If it is a buyer-initiated order, it is the positive sign, and vice versa.

e_i : the residual term of each equation.

imbalance has the predictability of the current stock return. Table 5 exhibits the percentages of significance in lag-one period under 95% confidence levels. It was found that only the average lag-one imbalance, δ_1, is significantly negative, while others are positive and insignificant. About 94.34% of the lag-one coefficients are negative, with 83.02% negative and significant under 5% confidence level.

This result is not consistent with Chordia and Subrahmanyam (2004). They observed that the first lag of imbalance has significant positively related to return while the further lagged imbalances are significant negatively related. There are three possible reasons for this discrepancy. First, there are different time horizons of the data. The study chooses the intraday data to replace the inter-day data used by Chordia and Subrahmanyam (2004). The order imbalances under different time zone present different patterns since the time interval in intraday data is too short to reveal market efficiency. Secondly, there are different characteristics of the sample. The study picks up only speculatively jump losers for the sample while Chordia and Subrahmanyam (2004) chose whole NYSE stocks for their samples. Llorente et al. (2002) address that when investors sell a stock for speculative reasons, its price decreases to reflect the negative private information. Since this information is usually only partially impounded into the price, the low return in the current period will be followed by a low return in the next period. Hence, the speculative trades would generate positively auto-correlated returns. Such characteristic, namely momentum effect, of the speculative stock is different from that of the samples of Chordia and Subrahmanyam (2004). Thirdly, market makers have the obligation to maintain a fair and orderly market. This becomes more important when extreme order imbalance exists. They have to adjust the bid-ask quote rapidly to stabilize the severe price volatility arising from the extreme order imbalance. Therefore, when market makers observe the abruptly increasing price due to huge positive order imbalance, they tend to adjust the bid-ask quote down. However, such adjustment will increase the inventory pressure of market makers because the lower quote is a bargain to speculative traders. However, during the adjusting process from market stabilization, the study finds a negative relationship between return and lag-one imbalance.

Dynamic volatility -order imbalance relation

Investors tend to ignore the accompanying risk with the profit they earn. Therefore, after observing the intraday return-order imbalance relationship, we are interested in examining the associated volatility. Table 6 shows the dynamic volatility-order imbalance relation. Average coefficient of volatility-order imbalance is -0.0304 and the standard deviation is 0.9688 while 88.68% (47 of the 53 sample firms) are concentrated in the group of -0.5 to 0.5. The study also finds that the percentage of positive and negative C_1's in the samples is almost the same, 26 C_1's are positive and 27 C_1's are negative. For the significant ones, the percentage of positive C_1 is 37.74% and 41.51% are negative ones.

Negative C_1 means that negative order imbalances are associated with positive order imbalance. As mentioned before, we expect the positive relation between volatility and order imbalances. However, the negative C_1's show against our intuition that higher order imbalance causes higher movement of stock price. Hence, we address three possible explanations, which are investors' behavior, leverage effect and small firm effect. First, this story is based on the prospect theory proposed by

Table 6. Empirical results of volatility-order imbalance relation in a GARCH (1,1) model.

	Percent positive (%)	Percent positive and significant (%)	Percent negative and significant (%)
β_1	100.00	100.00	0.00
C_1	49.06	37.74	41.51

"Significant" denotes significant at the 5% level.

$$R_t = \alpha_0 + \varepsilon_t$$

$$\varepsilon_t \middle| \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 * h_{t-1} + \beta_2 * \varepsilon_{t-1}^2 + C_1 * OI_t$$

R_t: the return on time t, defined as $\ln\left(\frac{P_t}{P_{t-1}}\right)$

OI_t: the order imbalance on time t. If it is a buyer-initiated order, it is the positive sign, and vice versa
ε_t: the residual term of the stock return, and is conditional on an information set of time t-1
h_t: the conditional variance on time t.

Kahneman and Tversky (1979). They discuss how investors evaluate potential loss and gain prospects. They argue that the utility function of investors for changes of wealth is normally concave when they gain and often convex when they lose. Given the same variation in value, the impact of losses is bigger than that of gains. That means when stock return is advanced by a positive order imbalance, people incline to hold the stock and wait. This tendency would decrease the volatility of the stock return. In contrast, when the negative order imbalance lowers the stock return, people would have the tendency to overreact and sell stocks in panic. Such behavior makes the volatility larger than that in the positive imbalance case. That means the negative relation between volatility and order imbalances of the half stocks may be attributed to the investors' irrational behaviors.

Secondly, Christie (1982) indicates that there is a negative relation between the volatility of the rate of return on equity and the value of equity. This phenomenon is in substantial part attributable to financial leverage. This can be explained that when stock price declines, the market capitalization of a company will drop off and the financial leverage ratio will increase to make the return more volatile. Thirdly, the negative volatility-order imbalance relationship may be related to the small firm effect. The lower stock price induced by large negative order imbalance increase the opportunities of speculators to affect the market price to gain abnormal return. Thus, the volatility may be higher by speculative trading.

Size effect

As Chordia and Subrahmanyam (2004) and Llorente et al. (2002) mentioned, firm size is usually considered to be a good proxy of information asymmetry. Because of fewer supervisors, such as shareholders and bondholders and only followed by fewer analysts, smaller firms are associated with more information asymmetry. In order to examine whether order imbalances generate much more return in small firms, we test the size effect. Table 7 shows that η_1 of $-8.382*10^{-8}$, the coefficient of market capitalization with α_1 as the dependent variable, is insignificant. One possible reason of this conclusion is the characteristics of the samples we chose. We find that 77.36% of our samples have the firm size of below 300 million. That is why we are not able to document a small firm effect in this study.

Order Imbalance-based trading strategies

Given the evidence of the strong relationship between return and order imbalance on the previous model, we test the profitability of the order imbalance-based trading strategies. The intraday rate of return of both strategies is shown in Table 8.

Strategy A: Buy at the trading price when OI is positive, and sell at the trading price when OI is negative

The study examines intraday returns from three different percentiles of order imbalances. The average return from no truncated order imbalances strategy is -101.26%, which is much lower than the average daily return of our samples, namely -44.01% on average. Nevertheless, the higher the percentile we truncated from order imbalance distribution, the higher the average portfolio return. By only picking up the order imbalances higher than the 99^{th} percentile of all imbalances, we enjoy a positive average return of 2.22% from the jump losers. It means that even the return is two standard deviation lower than the

Table 7. Empirical results of size effect.

	Average coefficient
η_1	-8.4E-08 (-0.8426)
θ_1	-7.6E-10 (-1.75818)

$$\alpha_{i1} = \eta_0 + \eta_1 * MKTCAP_i + \varepsilon_i$$

$$\gamma_{i0} = \theta_0 + \theta_1 * MKTCAP_i + \zeta_i$$

α_{i1} : the coefficient of sample stock i from the GARCH(1,1) model, i=1,2,… , 53.

γ_{i0} : the coefficient of sample stock i from the contemporaneous time-series regression, i=1,2,… , 53.

$MKTCAP_i$: the market capital of sample stock i, in million dollars.

ε_i and ζ_i : the residual terms of each regression.

Table 8. Intraday return-order imbalance-based trading strategies.

	Original (%)	> mean OI (%)	> 90% OI (%)	>99% OI (%)	No. of trade controlled (<5) (%)
Panel A					
Strategy A: Buy at trading price when OI >0 and sell at trading price when OI <0					
Mean	-101.26	-27.33	-11.16	2.22	7.78
Median	-75.12	-16.54	-7.61	0.00	5.62
Maximum	139.96	54.96	59.99	70.71	70.71
Minimum	-582.92	-207.14	-112.30	-18.01	-8.72
S. D.	111.56	44.76	33.16	14.76	13.22
Average No. of trade	386.5	107.9	59.6	6.3	2.5
Strategy B: Buy at the ask when OI >0, and sell at the bid when OI <0					
Mean	-187.47	-39.85	-16.05	3.60	8.54
Median	-143.92	-28.13	-17.93	0.00	5.55
Maximum	36.12	41.66	50.26	68.41	68.41
Minimum	-674.97	-152.41	-86.35	-14.66	-6.19
S. D.	143.64	40.10	27.11	13.37	12.37
Average No. of trade	387.9	107.9	59.4	6.3	2.6
Panel B: A profitability comparison of two strategies					
Percent	>0 96.23	86.79	79.25	41.51	49.06

average, the intraday return is still better than the daily return.

Furthermore, since the frequency of transactions of some stocks is still too high to execute practically, we heighten the critical imbalance to reduce the frequency down under five times. Through this adjustment, we control our average frequency of transaction to be 2.5 times. Our average return is improved to 7.78% with lower average standard deviation, 13.22%.

Strategy B: Buy ask when OI is positive, and sell at bid when OI is negative

Now, we turn to another more conservative strategy. After observing the dynamic change of the order imbalance, instead trading at the market traded price, we can only trade on the bid-ask quotation of market makers. It means that in the real world we would buy at higher price and sell at lower price than Strategy A. We also calculate

Table 9. Test of profitability difference of order imbalance-based trading strategies.

	c-value (%)	t-value
Strategy A: Buy at the trading price when OI>0, and sell at the trading price when OI<0		
	0	7.0659***
	50	3.8258***
	60	3.1777***
	70	2.5297***
	80	1.8817**
Strategy B: Buy at the ask when OI>0, and sell at the bid when OI<0		
	0	9.8980***
	130	3.3333***
	140	2.8283***
	150	2.3233**
	160	1.8184**
	170	1.3134*

Significance levels of 10, 5 and 1% are indicated by *, ** and *** respectively.

$R_{Controlled}$ - $R_{Origina}$	Strategy A (%)	Strategy B (%)
Mean	109.04	196.01
Median	79.35	150.03
Maximum	594.94	689.48
Minimum	-125.12	-21.27
S. Deviation	110.95	143.95
>0 (percentage)	96.23	98.11

$$\begin{cases} H_0: \mu_{\text{controlled}} - \mu_{\text{original}} \geq c \\ H_1: \mu_{\text{controlled}} - \mu_{\text{original}} < c \end{cases}$$

the intraday return with three different percentiles of order imbalances of all samples. We obtain -187.47% average original, lower than the one calculated from Strategy A as our expectation. By only picking up the order imbalances higher than the 99th percentile of all imbalances, we enjoy a high average return of 3.6% from the jump losers with 13.37% average standard deviation. Through the adjustment of frequency, our average frequency of transaction is lowered to 2.6 times. Our average return is improved to 8.54% with lower average standard deviation, 12.37%.

In Panel B of Table 9, we observe that the return of Strategy A is better than Strategy B in original, average and 90th percentile category of about 80 to 90% of our sample stocks. This result is consistent with our expectation. Nevertheless, the return in the 99th percentile and frequency truncated category cannot show the definite conclusion as other categories. There is one feasible explanation. The extreme order imbalance may affect quote so strongly that the trading price may be very close to the bid or ask quote to reflect the inventory pressure the market makers have. Therefore, in the extremely critical order imbalance case, the returns of both strategies are quite similar of about 7 to 8%.

More precisely, we further explore the profitability of two strategies using the paired comparisons t-test to see whether the return of extreme imbalance-truncated category is better than the non-truncated ones. We use frequency-truncated and original category as our variables. Table 9 shows the significance of our hypothesis under different c. The average return difference between frequency-truncated and non-truncated cases of Strategy A and Strategy B is 109.04% and 196.01%, respectively. In addition, almost 96% of our sample can have higher return through the extreme imbalance-selecting. Now we turn to focus on the results of our hypothesis. With less than 95% confidence level, the return of frequency-truncated ones is significantly 80% higher than the non-truncated case. Then we move to Strategy B, the return of frequency-truncated category is significantly 160% higher than the non-truncated case. The huge difference happens because the original return is too low in the Strategy B as our inference previously.

Nested return-order imbalance causality relation

In order to explore the reason behind successful

Table 10. Proportion of detected dynamic relationship between returns and order imbalances (%).

	$x_1 \wedge x_2$	$x_1 <-> x_2$	$x_1 \Rightarrow x_2$	$x_1 \Leftarrow x_2$	$x_1 <=> x_2$
Panel A: All trade size	0.00	22.64	11.32	39.62	26.42
Panel B: Firm size					
Small firm size	0.00	33.33	5.56	50.00	11.11
Medium firm size	0.00	17.65	11.76	47.06	23.53
Large firm size	0.00	16.67	16.67	22.22	44.44

truncated trading strategy, we examine the lead-lag relationship between return and order imbalance. 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 10, we present the results of tests of hypotheses on the dynamic relationship in Figure 1. Panel A presents results for the entire sample. In the entire sample, we show that a unidirectional relationship from returns to order imbalances is 11.32% of the sample firms for the entire sample, while a unidirectional relationship from order imbalances to returns is 39.62%. The percentage of firms that fall into the independent category is 0.00%.

Moreover, 22.64% of firms exhibit a contemporaneous relationship between returns and order imbalances. Finally, 26.42% of firms show a feedback relationship between returns and order imbalances. The percentage of firms reflecting a unidirectional relationship from order imbalances to returns is over three time than that from returns to order imbalances, suggesting that order imbalance is a good indicator for predicting future returns. It is consistent with many articles, which document that future daily returns could be predicted by daily order imbalances (Brown et al., 1997; Chordia and Subrahmanyam, 2004). In addition, the percentage of firms exhibiting a contemporaneous relationship is almost equal to that reflecting a feedback relationship, indicating that the interaction between returns and order imbalances on the current period is similar with that over the whole period.

In order to provide the evidence showing the impact on the relation between returns and order imbalances, in Panels B, we divide firms into three groups according to the firm size. Then we test the multiple hypotheses of the relationship between returns and order imbalances. The results in Panel B indicate that the unidirectional relationship from order imbalances to returns is 50.00% in the small firm size quartile, while the corresponding number is 22.22% in the large firm size quartile during the entire sample period. The size-stratified results 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, indicating that order imbalance could be a better indicator for predicting returns in small firm size quartile.

Conclusion

The relation between trading activity and market return has been explored extensively. Trading activity has usually been measured by volume, but the inventory paradigm, as Stoll (1978) and Spiegel and Subrahmanyam (1995) developed, suggests that the order imbalance could be a powerful determinant of price movement. The research examines the dynamic return-order imbalance relationship. The samples are the speculative jump losers during the whole year of 2005, totally 53 stocks. In this study, we focus on four topics: contemporaneous effect, lagged effect, volatility and size effect. Furthermore, we develop two trading strategies based on the order imbalance.

Firstly, the relation between contemporaneous order imbalance and stock returns is examined by GARCH (1,1) model and time-series regression model. Consistent with the evidence of previous studies, the data presents significantly positive relation no matter which model we adopt.

Secondly, by the similar time-series regression model, we turn to focus on the lagged effect of the return. Not as the result of Chordia and Subrahmanyam (2004), the relation between return and the lag-one order imbalance is negatively significant with or without including contemporaneous order imbalance in the model. The possible explanation is that our samples, speculative stocks, have the momentum effect. Additionally, the more previously imbalances, lag-two to lag-five period, have no effect on return because the inventory effects cannot last for long time horizons.

Thirdly, the study examines the volatility-order imbalance relationship by revised GARCH (1,1) model. The positive relationship is consistent with the expectation that larger imbalance would make return more volatile. The negative ones of some stocks is due to the investor behavior that they tend to hold their stocks when stock price going up, but tend to overreact and sell them in panic.

Fourthly, as Llorente et al. (2002) indicated, we consider the market capitalization for the degree of speculative trading. They argue that the stocks of smaller firms show a tendency for return continuation following high-volume days. Disappointedly, our result of the small firm effect is only significant under 90% confidence level. Accordingly, we can say that there may be small firm effect of the samples although we do not have very strong statistical result.

Given the evidence of the strong relationship between return and order imbalance on the previously presented model, we want to build up the order imbalance-based trading strategies to earn profit. Because of the characteristics of our samples, the extreme losers, we adopt the short selling strategy. It means we short sell a share if the negative order imbalance is observed and buy back a share if the order imbalance turns to be positive. We have two strategies based on different price matched to the imbalance: the trading price and bid-ask price, separately. The results show the huge profitability of our two strategies when we pick up only the extreme volume. All transactions ignore the transaction costs and taxes.

According to the causal relationship between return and order imbalance, we find that order imbalance is a good indicator for predicting future returns. Moreover, order imbalance could be a better indicator for predicting returns in small firm size quartile.

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