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Profitability and causality of order imbalance based trading strategy in hedge stocks

Abstract

For aggressive investors, their hedging actions (rotation) tend to result in abrupt price soaring and subsequent reversal in a short period. We try to screen the potential hedge targets and develop the associated trading strategies. The samples with maximum loss below 5% reveal a paradox of high potential upside and low downside. We find that hedgers seem to prefer specific sectors when screening potential rotation targets. We also document that the practice of "clearing the floats" plays a very important role in analyzing the waiting period for hedges and most price jumps, and also reversals are associated with volume augmentation.

Keywords: hedge, causality, information asymmetry, order imbalance.
JEL Classification: G12, G14.

Introduction

The studies of trading strategies remain one of the fascinating topics among the financial research areas (e.g., Jegadeesh and Titman, 1993, 2001; Chan, Jegadeesh and Lakonishok, 1996; Rouwenhorst, 1998; Chan, Hameed and Tong, 2000; Okunev, and White, 2003; Olson, 2004; Korajczyk and Sadka, 2004; Brzeszczynski and Gajdka, 2008; and Giacometti, and Rachev, 2008). To develop superior trading strategies for individual investors, it is essential to undertake in-depth research on certain anomalies or market practices and realize the underlying motivation, execution and potential risk. Therefore, one feasible trading strategy not only provides profitable opportunities, but represents the further understanding of certain phenomenon and its explanations.

According to Llorente, Michaely, Saar, and Wang (2002), investors trade for two reasons: to hedge and share risk and to speculate on the private information. For speculative investors, since their private information is usually partially impounded into the price, the low return in the current period will be followed by a low return in the next period. Thus, returns generated by speculative trades tend to continue themselves. For hedging investors, since the expectation of future payoff remains the same, the decrease in the price causes a low return in the current period and a high expected return for the next period. Thus, returns generated by hedging trades tend to reverse themselves.

The argument provides a theoretical explanation for certain hedge initiators. Due to the lack of consensus on market outlook or the pressure to reduce holdings when the next target is not yet decided, it is not unusual for most institutional investors, e.g., mutual funds and investment trusts to hedge conservatively by reallocating to money market instruments and simply cash, i.e. increase the asset classes of low risk, low return. However, as far as certain aggressive and return-oriented investors, e.g., hedge funds are concerned, an efficient hedge method with less fund idling is preferred, which is called rotation strategy (Kwasnica and K. Sherstyuk, 2007; Conover, Jensen, Johnson, and Mercer, 2008).

For aggressive investors with hedging needs, by predetermining the selection criteria according to particular inherent characteristics, a watch list of potential rotation targets is maintained. As the present investment overshoots or the upside is reached, such investors may respond immediately by rotating the investment to potential targets, boosting the price and dumping the position as uninformed investors or noise traders[1] rush in. Consequently, rotation actions tend to result in abrupt price soaring and subsequent reversal in a short period of time.

According to Chordia, Roll, and Subrahmanyam (2004), traders are inclined to split their orders over time to minimize the price impact of trades, thus, causing positive autocorrelation in equilibrium imbalances. In turn, this autocorrelation causes intertemporal correlation in price pressures which gives rise to a positive predictive relation between imbalances and future returns. They indicate that imbalance-based trading strategies yield statistically significant profits before accounting for brokerage commissions[2].

Moreover, information asymmetry has a significant influence on return-order imbalance relation. Lo and MacKinlay (1990) and Llorente et al. (2002) use firm size to measure information asymmetry. They argue that firms with larger size have a lower degree

[1] Following Kyle (1985), Black (1986) defines "noise traders" as the investors, with no access to inside information, irrationally acting on noise as if it were information that would give them an edge.
[2] Nonetheless, Chordia, Roll, and Subrahmanyam (2008) find that such profits are diminished when bid-ask spread are narrower, and has declined over time with the minimum tick size.

of information asymmetry. The larger the firm sizes are, the more regulations, debt holders, equity holders and analysts are involved in. Easley et al. (1996) document that low volume stocks have higher probabilities of informed trading.

The purpose of this study is to investigate the selection criteria and rationales and develop a corresponding free-riding trading strategy. By tracking the price movement under such strategy, the inherent characteristics and return pattern of rotation targets can be further clarified. In addition, GARCH(1,1) model is introduced to capture the time variant property of return, volatility and the significance of order imbalance in explaining stock returns. Finally, we develop a story of dynamic lead-lag relationship to explain the abnormal return from our strategy. According to Chen and Wu (1999), we define five groups of dynamic relationship, including independency, the contemporaneous relationship, unidirectional relationship and feedback relationship. To determine a specific causal relationship, we use a systematic multiple hypotheses testing method. Unlike the traditional hypothesis testing, this testing method avoids the potential bias induced by restricting the causal relationship to a single alternative hypothesis.

The rest of this study is organized as follows. In section 1 data is presented, while section 2 provides a methodology. Our empirical results are shown in section 3. The final section concludes.

1. Data

Due to the importance of the index and the coverage by analysts worldwide, NASDAQ market offers highly transparent information. Any private information leakage will reflect on the stock price efficiently, and thus, eliminate the differential between share price and intrinsic value. Such characteristic can help improve the reliability of research results.

The transaction data sources are Center for Research in Security Price (CRSP) and New York Security Exchange TAQ (Trades and Automated Quotations). The sample period covers Jan. 1, 2003 to Nov. 30, 2005. Stocks are included depending on the following criteria. Sampled stocks focus on ordinary equities. Assets in the following categories are excluded: certificates, ADRs, shares of beneficial interest, units, closed-end funds, preferred stocks, and REITs. Such criterion can rule out the possibility that the trading characteristics and mechanism of different securities have its particular influence on the price behavior.

Preliminary samples include 2368 NASDAQ common stocks during 2003-2005. The transaction data are included according to the following criteria. A trade or quote is excluded if it is recorded before the open or after the closing time (i.e. intraday data is collected from 9:30 AM to 16:00 PM.). Such criterion can also rule out the possibility that trading mechanism in other trading hours has different influence on the price behavior. Quotes less than \$0.01 are discarded. Negative bid-ask spreads are discarded. Following Lee and Ready (1991)[1], any quote less than 5 seconds prior to the trades is ignored and the first one at least 5 seconds prior to the trade is retained.

2. Methodology

2.1. GARCH model. In order to examine intraday time varying relations between volatility, return and order imbalance, we employ a GARCH model:

$$\begin{aligned} R_t &= \alpha_0 + \alpha_1 * OI_t + \varepsilon_t \\ \varepsilon_t | \Omega_{t-1} &\sim N(0, h_t) \\ h_t &= A + B_1 * h_{t-1} + C_1 * \varepsilon_{t-1}, \end{aligned} \tag{1}$$

where R_t is the return in period t, defined as ln (P_t / P_{t-1}), OI_t is the order imbalance variable in period t, ε_t is the residual of the stock return in period t, h_t is the conditional variance in period t, and Ω_{t-1} is the information set in period t-1.

2.2. Multiple regression models. The multiple regression models are listed below to examine contemporaneous and lagged return-order imbalance relations.

2.2.1. Contemporaneous order imbalance model.

$$\begin{aligned} R_t = a + b_t OI_t + b_{t-1} OI_{t-1} + b_{t-2} OI_{t-2} + \\ b_{t-3} OI_{t-3} + b_{t-4} OI_{t-4}, \end{aligned} \tag{2}$$

where R_t is the stock return in period t, OI_t is the order imbalance variable in period t.

2.2.2. Lagged order imbalance model.

$$\begin{aligned} R_t = a + b_{t-1} OI_{t-1} + b_{t-2} OI_{t-2} + b_{t-3} OI_{t-3} + \\ b_{t-4} OI_{t-4} + b_{t-5} OI_{t-5}, \end{aligned} \tag{3}$$

where R_t is the current stock return in period t, OI_t is the order imbalance variable in period t.

Following the arguments of Chordia et al. (2004), multiple regression models are employed to ex-

[1] Using the Lee and Ready (1991) algorithm, every transaction is assigned based on the following rules. A trade is classified as buyer (seller) initiated if it is closer to the ask (bid) of prevailing quote. If the trade is exactly at the midpoint of the quote, a "tick test" classifies the trade as buyer (seller) initiated if the last price change prior to the trade is positive (negative).

amine the relationship between stock return and lagged order imbalance. The only difference between the two equations is that the contemporaneous model introduces current order imbalance as an explanatory variable and lagged model comprises simply lagged order imbalance. While both regression models conceptually resemble each other, the lagged model may provide the potential predictability in stock return. Namely, if the relationship between stock return and lagged order imbalance can be identified, lagged imbalance may be utilized to develop an imbalance-based trading strategy.

2.3. The nested causality between return and order imbalance. In order to explain the story behind order imbalance based trading strategy, we employ a nested causality to explore the dynamic causal relation between return and order imbalance. According to Chen and Wu (1999), we define four relationships 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

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

and $$Var(x_{2(T+1)} | \underset{\sim}{x_2}) = Var(x_{2(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}) = Var(x_{2(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{1(T+1)}}). \quad (5)$$

Definition 2: Contemporaneous relationship, $x_1 <-> x_2$: x_1 and x_2 are contemporaneously related if

$$Var(x_{1(T+1)} | \underset{\sim}{x_1}) = Var(x_{1(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}), \quad (6)$$

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

and $$Var(x_{2(T+1)} | \underset{\sim}{x_2}) = Var(x_{2(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}), \quad (8)$$

$$Var(x_{2(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}) > Var(x_{2(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{1(T+1)}}). \quad (9)$$

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

There is a unidirectional relationship from x_1 to x_2 if

$$Var(x_{1(T+1)} | \underset{\sim}{x_1}) = Var(x_{1(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}), \quad (10)$$

and $$Var(x_{2(T+1)} | \underset{\sim}{x_2}) > Var(x_{2(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}). \quad (11)$$

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

There is a feedback relationship between x_1 and x_2 if

$$Var(x_{1(T+1)} | \underset{\sim}{x_1}) > Var(x_{1(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}), \quad (12)$$

and $$Var(x_{2(T+1)} | \underset{\sim}{x_2}) > Var(x_{2(T+1)} | \underset{\sim}{x_1}, \underset{\sim}{x_2}). \quad (13)$$

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

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

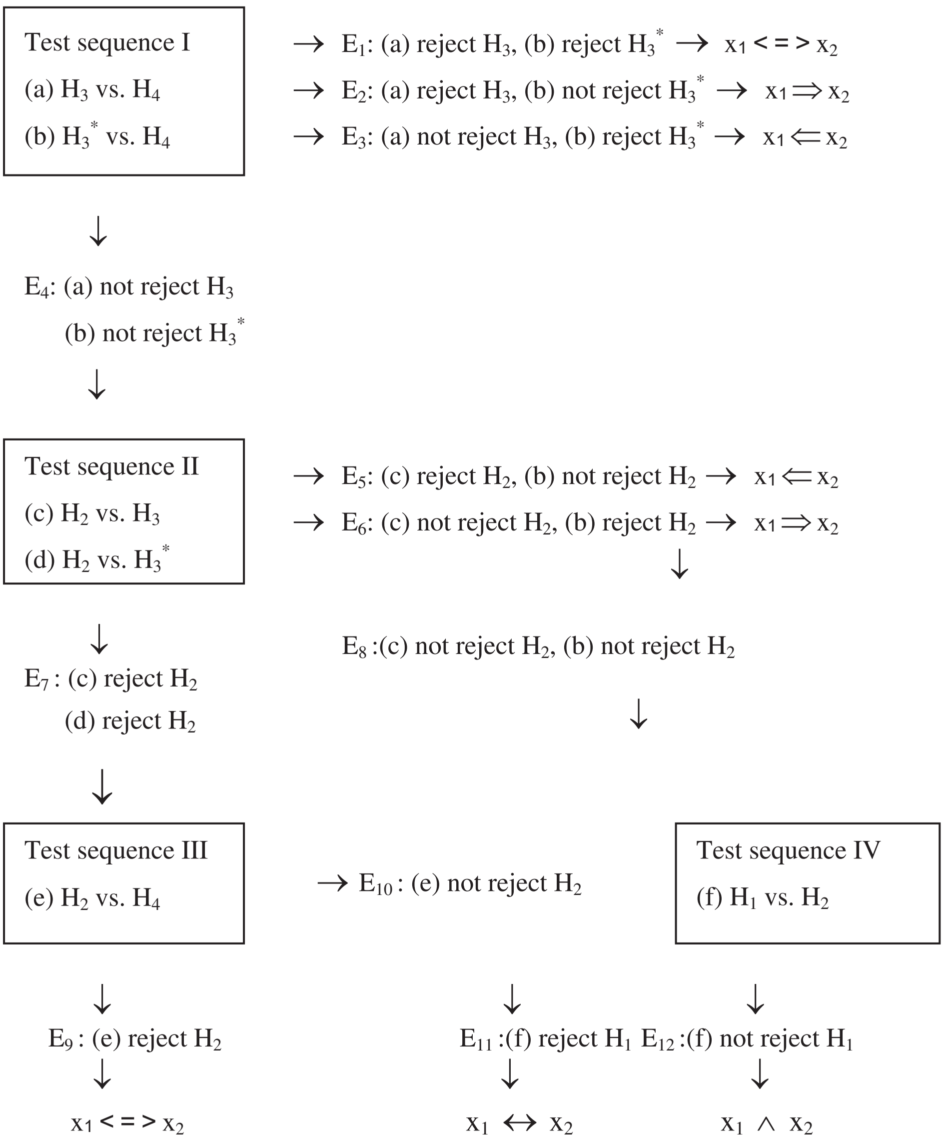
The bivariate VAR model:
$\begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$, where x_{1t} and x_{2t} are mean adjusted variables. The first and second 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 $\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$.

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 $\sigma_{12}=\sigma_{21}=0$

To determine a specific causal relationship, we use 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, we employ results of several pair-wise hypothesis tests.

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

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



3. Empirical results

3.1. Profitability on trading strategies. The trading signal appears for five consecutive trading days, and the open price on the fifth trading day is regarded as the holding cost. With regard to each price jump, if the trading signal appears for several trading days, all the trading days are sampled. By including all trading signals, the return pattern and results can be observed under a strictly rule-based trading strategy.

Under the less strict volume declining criteria, e.g., below the moving average volume, Table 3 presents total trading signals in each year occur 267 to 355 times and average daily trading signals are 2.08-2.34 times. Under the more strict volume declining criteria, below 80% of the moving average volume, total trading signals in each year occur 60 to 104 times in the sample period, and average daily trading signals are 1.27-1.55 times. The average daily trading signals are computed by averaging the trading signals only if signals appear on the trading day. Such definition helps understand how many potential targets may appear if trading signals occur on the trading day.

Table 3. Descriptive statistics of all samples

Sample period	2003		2004		2005	
Volume declining criteria	100%	80%	100%	80%	100%	80%
Total trading signals	267	60	355	63	343	104
Average daily trading signals	2.09	1.27	2.34	1.55	2.08	1.27
Mean of the maximum return in holding period	29.0%	16.2%	25.0%	21.6%	18.4%	20.3%
Median of the maximum return in holding period	18.1%	15.0%	14.5%	16.5%	15.2%	16.7%
Hit rate	68.9%	55.0%	61.4%	74.6%	63.0%	68.3%

The results reveal that altering the extent of volume declining can impact the amount of trading signals significantly. It is noted that regardless of the extent of volume declining, average daily trading signals occur only 1-2 times, which indicates that the samples are distributed evenly across the trading days of the sample period. The maximum return is based on the holding cost and the highest price in the holding period. When the volume declining criterion is set to be below the moving average volume, the mean (median) of the maximum return in each year ranges from 18.4% (14.5%) to 29% (18.1%). Due to the astonishing price jump of certain rotation targets on the event day, the mean is obviously higher than the median. Relatively, the median seems to be more stable and, thus, a more appropriate indicator.

The maximum return in each year all presents right-skewed distributions, and most returns concentrate between 0% and 20%. We define the hitting rate as the percentage of samples with maximum return above 10% out of total samples. Such definition helps evaluate the efficiency of the selection criteria in improving sample return. Under the less strict volume declining criteria, below the moving average volume, the hitting rates are around 61.4%-68.9%. Under the more strict volume declining criteria, below 80% of the moving average volume, the hitting rates range 55%-74.6%. The results indicate that the more strict volume declining criterion increases the hit rate in 2004 and 2005, which implies that in the samples with lower trading volume, a larger proportion shows higher return. Although the more strict volume declining criteria can increase the hit rate, i.e. reduce the amount of false alarms, qualified samples decrease significantly. Therefore, the tradeoff arises between the hit rate and the number of samples.

3.1.1. Samples with maximum return above 10%. The trading signal appears for five consecutive trading days, and the open price on the fifth trading day is regarded as the holding cost. The maximum return exceeds 10% in the one month holding period. With regard to each price jump, if the trading signal appears for several trading days, only the first trading day is sampled. By including only one trading signal, the return pattern and results can be observed under an event study method, rather than following a rule-based trading strategy.

Panel A of Table 4 presents the mean and median of samples with maximum return above 10%. About 70 samples possess the maximum return above 10% in the one month holding period each year. For these samples, the mean (median) of the maximum return in each year ranges from 25.5% (18.9%) to 31.5% (22.8%). We define the maximum loss in one month holding period as follows:

$$\textit{The maximum loss} = \textit{Min}\{0, (\textit{Daily Low Price-Holding Cost})/\textit{Holding Cost}\} \quad (14)$$

Panel B of Table 4 presents the distribution of the maximum loss. More than half of the samples possess the maximum loss below 5% in the one month holding period, while stocks with maximum loss above 10% also account for one-third of the samples.

Table 4. Samples with maximum return above 10%

Panel A. Descriptive statistics			
Sample period	2003	2004	2005
Sample size	74	70	68
Mean of the maximum return in holding period	31.5%	42.4%	25.5%
Median of the maximum return in holding period	22.8%	20.8%	18.9%
Panel B. Distribution of maximum loss in holding period			
Sample period	2003	2004	2005
0.0%	28.4%	18.6%	16.2%
-5.0%	13.5%	24.3%	17.6%

Table 4 (cont.). Samples with maximum return above 10%

Sample period	2003	2004	2005
-10.0%	14.9%	7.1%	10.3%
-15.0%	14.9%	25.7%	26.5%
Panel C. Distribution of sectors			
Sample period	2003	2004	2005
Chemical manufacturing	17.6%	15.7%	17.6%
Computer and electronic product manufacturing	17.6%	21.4%	23.5%
Professional, scientific, and technical services	13.5%	12.9%	14.7%
Miscellaneous manufacturing	5.4%	4.3%	7.4%

For samples with the maximum loss below 5%, the results reveal a paradox of high upside and low downside. Possible explanations are as follows: for the samples under such selection criteria, provided that the stock is chosen as a rotation target during the holding period, the stock price tends to sky-rocket and, thus, shows high upside. However, if the stock is not chosen, its inherent stability prevents the stock price from slumping and, thus, shows low downside.

For samples with the maximum loss above 10%, possible explanations and strategic suggestions are as follows: if the maximum loss occurs prior to the price jump, the loss may result from the process of "clearing the floats" before the rotation action. Investors are suggested to hold the position until hedge initiators finish the process to avoid the loss. However, if the maximum loss occurs posterior to the price jump, the loss may be attributed to the price reversal after the rotation action, as illustrated in Llorente et al. (2002). Investors are suggested to sell out all the positions to avoid the reversal as soon as the price jumps.

Panel C of Table 4 presents the distribution of sector. Chemical manufacturing, computer and electronic product manufacturing, professional, scientific, and technical services in each year account for more than half of the samples. Such feature suggests that hedge initiators seem to prefer specific sectors when screening potential rotation targets.

3.1.2. The first trading day with maximum return above 10%. Using the samples selected in the previous section, we highlight the return pattern of the first trading day with the maximum return above 10%. The purpose to observe the first trading day with the maximum return above 10% is described as follows: for a number of samples with maximum return above 10%, a pattern is found that the maximum return tends to exceed 10% for more than one trading day in the holding period. Focusing on the first price jump helps ensure that the jump mainly results from the inherent characteristics of rotation targets, e.g., stationary price, declining volume and low price. The subsequent price increase may arise from the herding of uninformed noise traders or momentum-based speculators after the price jump, and it requires further investigation to clarify the reasons.

Panel A of Table 5 presents the mean and median of samples on the first trading day with the maximum return above 10%. For the first trading day with daily return above 10%, the mean (median) of the returns in each year ranges from 14.1% (12.6%) to 16.4% (13.9%). Compared to the maximum return in the one month holding period, the first daily return above 10% is obviously lower, which reveals that the maximum return in the holding period should occur after the first jump. The subsequent price increase may imply the possibility of speculation following the rotation action. We define the waiting period as the trading days between the purchase day and the first day with daily return above 10%. "Clearing the floats" plays a key role in analyzing the waiting period. Based on the holding cost and close prices prior to the first price jump, the samples are partitioned into two groups. For the group, in which the close price used to fall below the holding cost, the average waiting period ranges from 10.5 to 12.1 trading days. For the group, in which the close price did not fall below the holding cost, the average waiting period ranges from 4.2 to 4.6 trading days. "Clearing the floats" is a common practice that hedge initiators tend to purposely depress the price of potential targets before a large amount of fund is invested. Such trick forces the floats to close out the position to stop loss, which prevents the selling pressure of profit-taking floats and, thus, magnifies the price boost. The price downtrend before the first jump may imply that the rotation target used to experience "clearing the floats". Hedge initiators need to wait until the floats can not bear the loss and close out the position, and, thus, result in a longer waiting period.

Table 5. Samples in first trading day with maximum return above 10%

Panel A. Descriptive statistics			
	2003	2004	2005
Sample size	74	70	68
Mean of the return	14.1%	15.6%	16.4%
Median of the return	12.6%	12.7%	13.9%
Waiting period (days)			
Close price used to fall below the cost	10.5	11.2	12.1
Close price not used to fall below the cost	4.6	4.3	4.2
Panel B. Distribution of volume augmentation			
Volume augmentation	2003	2004	2005
5	59.5%	47.1%	50.0%
10	12.2%	17.1%	20.6%
Panel C. Distribution of close price reversal			
Close price reversal	2003	2004	2005
10%	25.7%	17.1%	20.6%
20%	16.2%	25.7%	16.2%

On the contrary, the stable price before the first jump may imply that floats are fewer and "clearing the floats" is not necessary. In such circumstance, hedge initiators can perform the rotation directly, and, thus, result in a shorter waiting period.

Panel B of Table 5 presents the distribution of volume augmentation. On the first trading day with the maximum return above 10%, stocks with one to five-fold volume comparing to the previous trading day account for 47.1%-59.5% of the samples, and stocks with five to ten-fold volume account for 12.2%-20.6%. The results reveal that most price jumps are likely to accompany volume augmentation.

Panel C of Table 5 presents the distribution of the close price reversal. The close price reversal on the event day is defined as follows:

$$\textit{Close price reversal} = (\textit{daily high price} - \textit{close price}) / (\textit{daily high price} - \textit{holding cost}). \quad (15)$$

On the first trading day with the maximum return above 10%, stocks with 0%-10% price reversal account for 17.1%-25.7% of the samples, and stocks with 10%-20% price reversal account for 16.2%-25.7%. Most samples show price reversal on the event day, which verifies the arguments of Llorente et al. (2002) that returns generated by hedging trades tend to reverse themselves.

3.2. Intraday time varying volatility, return and order imbalance. From the first trading day with maximum return above 10%, samples with the daily return above 10% are chosen in GARCH model. Under the above criteria, one hundred stocks are sampled. Among the samples, quotes for three stocks are not available and two stocks possess less than thirty quotes. Hence, five stocks are excluded and ninety-five stocks are sampled in total.

Seventy-three out of ninety-five samples show positive order imbalance sum. The results indicate that for most rotation targets, buyer-initiated orders tend to exceed seller-initiated orders on the jump day. The average of intraday return mean for all samples is 0.0157%. It is noted that the average is close to zero since the order-to-order time interval is extremely short. In addition, the positive sign shows that the price of rotation targets tends to soar on the event day.

Panel A of Table 6 summarizes the results of significance of the relationship between order imbalance and stock return (volatility). We find that stocks with positive order imbalance coefficients account for 89.4% of the samples, which reveal that order imbalance has a positive influence on stock return. Under the 95% confidence level, 85.1% of the samples are positive and significant. The results indicate that order imbalance indeed presents significant influence on most samples on the event day, which is coincident with the expectation. Under the 95% confidence level, more than 90% are significant, indicating that order imbalances indeed present significant influence on return volatility for most samples on the event day. However, the direction of influence on return volatility fails to present consistency. Under the 95% confidence level, 45.3% of the samples are positive and significant and 50.5% are negative and significant.

Table 6. Significance of the relationship between order imbalance and return (volatility)

	Percent positive	Percent positive and significant	Percent negative and significant
Panel A. GARCH model			
Stock return	89.40%	85.10%	7.40%
Volatility	48.50%	45.30%	50.5%

Table 6 (cont.). Significance of the relationship between order imbalance and return (volatility)

Panel B. OLS model with contemporaneous order imbalance			
Percent positive	Percent positive and significant	Percent negative and significant	Percent positive
Lag 0	97.92%	86.46%	0.%
Lag 1	5.21%	0%	76.01%
Lag 2	54.17%	4.17%	7.30%
Lag 3	66.67%	4.17%	1.04%
Lag 4	53.13%	2.09%	3.13%
Panel C. OLS model without contemporaneous order imbalance			
Lag 1	45.83%	37.5%	39.58%
Lag 2	36.46%	2.08%	33.33%
Lag 3	60.42%	2.08%	3.13%
Lag 4	59.38%	16.67%	2.08%
Lag 5	56.30%	7.29%	3.13%

In the imbalance-based trading strategy, the intraday order imbalance is employed as the trading indicator. When a negative order imbalance appears, the corresponding ask price is regarded as the buying price. The stock is held until the order imbalance turns positive and the corresponding bid price is regarded as the selling price. Afterward, another round of trading will start over when the order imbalance turns negative again. This trading strategy is executed throughout the trading day and returns in each round are summed. The imbalance-based trading strategy for rotation targets is inspired by the interaction between discretionary traders and market makers. When substantial positive order imbalance appears, market makers soon realize that the rising price results from the buying action of certain discretionary traders. With sufficient inventory available at hand, market makers tend to deliberately depress the stock price (order imbalance would turn negative) to force the discretionary trader to close out the position at a lower price. Therefore, to develop a trading strategy for rotation targets, it is more reasonable to buy at negative order imbalance and sell at positive order imbalance.

3.3. Contemporaneous and lagged effect. Panel B of Table 6 summarizes the significance of contemporaneous order imbalance. By comparing the results with those of GARCH model, it is noted that the outcome resembles each other. Under the confidence level of 95%, more than 80% of the samples present positive significance in contemporaneous imbalance variable. The results are consistent with those of Chordia et al. (2004). It is once again proved that contemporaneous order imbalance indeed presents significant influence on most samples.

Panel C of Table 6 summarizes the significance of lagged order imbalance. Under the 95% confidence level, more than 70% of the samples are significant in lagged-one imbalance. However, the direction of influence on stock return fails to present consistency with that of contemporaneous imbalance variable. 39.6% of the samples present positive and significant and 44.8% present negative and significant. The results are not consistent with those of Chordia et al. (2004), which indicated that a positive (and, thus, predictive) relation exists between returns and lagged imbalances when contemporaneous imbalances are not included in the regression. Therefore, to utilize lagged order imbalance as a predictive indicator of stock return, it requires further investigation to clarify the direction of influence before developing an imbalance-based trading strategy.

3.4. Return-order imbalance causality relationship in explaining the successful trading strategy. To explore the reason why an order imbalance trading strategy earns a significant abnormal return, we employ a nested causality approach. In order to investigate a dynamic relationship between two variables, we impose the constraints in the upper panel of Table 1 on the VAR model. In Table 7, we present the empirical results of tests of hypotheses on the dynamic relationship in Table 2. Panel A presents results for the entire sample. In the entire sample, we show that a unidirectional relationship from returns to order imbalances is 15.63% of the sample firms for the entire sample, while a unidirectional relationship from order imbalances to returns is 18.75%. The percentage of firms that fall into the independent category is 8.33%. Moreover, 42.71% of firms exhibit a contemporaneous relationship between returns and order imbalances. Finally, 14.58% of firms show a feedback relationship between returns and order imbalances. The percentage of firms carrying a unidirectional relationship from order imbalances to returns is larger than that from returns to order imbalances, suggesting that order imbalance is a better 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, Walsh, and Yuen, 1997; Chordia et al., 2004). In addition, the percentage of firms exhibiting a contemporaneous relationship is about three times than that reflecting a feedback relationship, indicating that the interaction between returns and order imbalances on the current period is larger than that over the whole period.

Table 7. Dynamic nested causality 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 size					
All trade size	8.33%	42.71%	15.63%	18.75%	14.58%
Panel B. Firm size					
Small firm size	15.63%	59.38%	15.63%	6.25%	3.13%
Medium firm size	3.13%	43.75%	18.75%	25.00%	9.38%
Large firm size	6.25%	25.00%	12.50%	25.00%	31.25%

In order to provide the evidence showing the impact on the relation between returns and order imbalances, in Panel 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 6.25% in the small firm size quartile, while the corresponding number is 25.00% 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 larger, the percentage of firms exhibiting a unidirectional relationship from order imbalances to returns is higher, indicating that order imbalance is a better indicator for predicting returns in large firm size quartile.

Conclusions

For samples with maximum loss below 5%, the results reveal a paradox of high upside and low downside. For samples with maximum loss above 10%, such loss can be attributed to the practice of "clearing the floats" or the price reversal, depending on the timing of the loss. Moreover, top three sectors in each year account for more than half of the samples. This feature suggests that hedge initiators seem to prefer specific sectors when screening potential rotation targets.

Comparing with the maximum return in the holding period, the first daily return above 10% is obviously lower, which reveals that the maximum return in the holding period should occur after the first jump. The subsequent price increase may imply the possibility of speculation following the rotation action. Moreover, "clearing the floats" plays a key role in analyzing the waiting period. The price downtrend before the first jump may imply that the rotation target used to experience "clearing the floats", and thus a longer waiting period is observed. Lastly, the results reveal that most price jumps are likely to accompany volume augmentation, and most samples show price reversal on the event day, which verifies the arguments in Llorente et al. (2002) that returns generated by hedging trades tend to reverse themselves.

In our intraday time varying volatility, return and order imbalance relation, we document that under the confidence level of 95%, 92.6% of the samples present significance, and 85.1% of them are positively significant. The results indicate that order imbalance indeed presents significant influence on most samples on the event day, which is coincident with the expectation.

References

1. Black F. Noise // *Journal of Finance*, 1986. – № 41. – pp. 529-543.
2. Brown, P., D. Walsh, A. Yuen. The Interaction between Order Imbalance and Stock Price // *Pacific-Basin Finance Journal*, 1997. – № 5. – pp. 539-557.
3. Brzeszczynski, J., J. Gajdka. Performance of High Dividend Yield Investment Strategy on the Polish Stock Market 1997-2007 // *Investment Management and Financial Innovations*, 2008. – № 2. – pp. 86-92.
4. Chan, K., N. Jegadeesh and J. Lakonishok. Momentum Strategies // *Journal of Finance*, 1996. –№ 51, 1681-1713.
5. Chan, K., A. Hameed and W. Tong. Profitability of Momentum Strategies in the International Equity Markets // *Journal of Financial and Quantitative Analysis*, 2000. – № 35. – pp. 153-172.
6. Chen C., C. Wu. The Dynamics of Dividends, Earnings and Prices: Evidence and Implications for Dividend Smoothing and Signaling // *Journal of Empirical Finance*, 1999. – № 6. – pp. 29-58.
7. Chordia, T., A. Subrahmanyam. Order Imbalances and Individual Stock Returns: Theory and Evidence // *Journal of Financial Economics*, 2004. – № 72. – pp. 485-518.
8. Chordia, T., A. Subrahmanyam. Liquidity, and Market Efficiency // *Journal of Financial Economics*, 2008. – № 87, – pp. 249-268.
9. Conover, C.M., G.R. Jensen, R.R. Johnson, and J.M. Mercer. Sector Rotation and Monetary Conditions // *Journal of Investing*, 2008. - № 17. – pp. 34-46.
10. Easley, D., N.M. Kiefer, M. O'Hara, and J. Paperman. Liquidity, Information, and Infrequently Traded Stocks // Journal of Finance, 1996, – № 51, – pp. 1405–1436.
11. Giacometti, R., S. T. Rachev. Funds of Hedge Funds: A Comparison among Different Portfolio Optimization Models Implementing the Zero-Investment Strategy // *Investment Management and Financial Innovations*, 2008. – № 3, – pp. 19-29.

12. Jegadeesh, N., and S. Titman, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency // *Journal of Finance*, 1993. – № 58. – pp. 65-91.
13. Jegadessh, N., and S. Titman, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations // *Journal of Finance*, 2001. – № 56. – pp. 699-720.
14. Korajczyk. R., and R. Sadka, Are Momentum Profits Robust to Trading Costs? // *Journal of Finance*, 2004. – № 59. – pp. 1039-1082.
15. Kwasnica, A.M., and K. Sherstyuk. Collusion and Equilibrium Selection in Auctions // *Economic Journal*, 2007. – № 117. – pp. 120-145.
16. Kyle, A.S. Continuous Auctions and Insider Trading // Econometrica, 1985. – № 53, – pp. 1315-1336.
17. Lee, C., M. Ready. Inferring Trade Direction from Intraday Data // *Journal of Finance*, 1991. – № 46. – pp. 733-747.
18. 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.
19. Lo, A. and C. MacKinlay. When are Contrarian Profits due to Stock Market Overreaction // *The Review of Financial Studies*, 1990. – № 3, – pp. 175–205.
20. Okunev, J., and D. White. Do Momentum-Based Strategies Still Work in Foreign Currency Markets // *Journal of Financial and Quantitative Analysis*, 2003. – № 38. – pp. 425-447.
21. Olson, D. Have Trading Rule Profits in the Currency Market Declined over Time? // *Journal of Banking and Finance*, 2004. – № 28. – pp. 85–105.
22. Rouwenhorst, K. International Momentum Strategies // *Journal of Finance*, 1998. – № 53. – pp. 267-284.