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Abstract

This paper selects the hedging stocks as the sample stocks using the criteria of stationary price, declining volume and price range. The results show that more than 50% of the samples have significant positive correlation between order imbalances and stock return in five to ten-minutes time interval, but only 30.95% in fifteen-minute time interval, which implies that the market is getting more efficient as the time interval becomes longer. The imbalances-based trading strategy we develop is if order imbalances are positive, we long this stock, and sell it when the order imbalances turn negative. The result presents that the return from truncated trading strategy is better than non-truncated one. In order to explore dynamic relation between return and order imbalance, we employ a nested causality approach. The percentage of firms carrying a unidirectional relationship from order imbalances to returns is smaller than that from returns to order imbalances.

Keywords: order imbalance, information asymmetry, volatility, market efficiency, causality relationship.
JEL Classification: G12, G14.

Introduction

Every investor in the stock market tries to maximize his profit in the stock market. According to Chordia et al. (2002), positive autocorrelation exists for order imbalances. Furthermore, the contemporaneous and lagged imbalances are strongly related to the current stock returns. Llorente et al. (2002) argued that investors trade mostly for hedging and speculative purposes. For those who hedge, if the price of the stocks in their hands overshoots or reaches its upside, they will execute the rotation strategy, or basically switch to buy some other stocks, and price of the newly purchased stocks would then experience a quick soar followed by a correspondingly drastic drop-off as the noise trader rush in. Since the price and the trading volume of these stocks experience such abrupt changes in price, they are worth investigating in detail, and this is the major purpose of this study.

In addition, market efficiency is always an important concern for stock market investors since efficiency market hypothesis (EMH)[1] asserts that only fundamental factors could affect the stock price. According to Chordia et al. (2005), market efficiency could be improved by sophisticated investors who track and react to the order imbalances by countervailing trade[2]. In this study, we explore if the relationship between order imbalances and stock returns exists and if so, for how long such an effect would persist.

We confirm a positive return-order imbalance relation in hedge stocks. However, the number of positively significance of lagged order imbalance on stock return decreases as time interval goes longer. From contemporaneous order imbalance model, we note that contemporaneous order imbalance actually plays an important role in explaining the stock returns in all time intervals. In the 95% confidence level, more than 80% of the contemporaneous order imbalances have positive influences on stock returns, and at least 45% are significantly positive in all time intervals. In addition, we also find that more than 50% of the lagged one order imbalances have a negative impact on current hedge stock returns. The result is consistent with Chordia and Subrahmanyam (2004).

According to our intraday results, percentage of significant positive order imbalances decreases from 71.4% to 26.2% as the time interval increases, suggesting that as the time interval increases, the effect of order imbalances on stock returns gradually dies out. The situation provides powerful evidences that the market is getting more efficient as the time interval becomes longer. Moreover, at the 95% confidence level, percentage of positive and significant coefficients is 71.4% in GARCH model in five-minute interval, but it is only 66.7% in OLS model. This result is out of our expectation. One possible explanation is that investors pay more attention to order imbalances and ignore the risk as the stock price goes up in the very short term (for example, five-minute interval).

In general, large order imbalances are positively associated with large volatilities of stock returns. We expect there is a positive correlation between them. Nonetheless, the empirical results surprise us.

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[1] Ozdemir (2008) shows that the Istanbul Stock Exchange National 100 (ISEN 100) price index is characterized by a unit root with two structural breaks, which is consistent with the efficient market hypothesis.
[2] From the perspective of market inefficiency, Chordia et al. (2005) show that the market does not converge to efficiency immediately. Grossman (1975) and Grossman and Stiglitz (1980) find that the market prices cannot fully incorporate all knowable information. They argue that someone must be able to generate returns by exploiting the deviation of prices from fundamental values.

We find that nearly 50% of our sample stocks exhibit a negative relation between order imbalance and volatility. We attribute this unexpected result to price stabilization from market makers, whose most important responsibility is to maintain the stability of stock prices. When market makers are smart enough to discover private information through order imbalance or are abundantly endowed in inventories and funds, they adjust price movements to beat informed traders and noise traders.

We develop a trading strategy based on order imbalances and see whether or not a trading strategy generates abnormal returns. The imbalance-based trading strategies are not able to beat buy-and-hold return. In order to explain the story behind empirical results, we employ a nested causality to explore dynamic causal relation between return and order imbalance. The percentage of firms carrying a unidirectional relationship from order imbalances to returns is smaller than that from returns to order imbalances, suggesting that order imbalance is not a better indicator for predicting future returns. It is not 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; Su et al., 2008; Kim and Masulis, 2011, Huang and Tung, 2013). In addition, the percentage of firms exhibiting a contemporaneous relationship is about eight 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.

The study is organized as follows. Section 1 describes the data. Methodology is explained in section 2. Section 3 discusses empirical results and the final section concludes the paper.

1. Data

We collect intraday transaction data of hedge stocks from Center for Research in Security Price (CRSP) and New York Security Exchange TAQ (Trade and Automated Quotation).

1.1. Selection criteria for hedging stocks. According to Su et al. (2010), the selection criteria for the sample stocks are as follows. First, the highest and lowest price in the past 30 transaction days stay within the range of upper and lower 20% of the average close price. Second, the highest and lowest price in the past 90 transaction days can not stay within the range of upper and lower 20% of the average close price. Third, daily trading volume has to be less than the moving average volume of the past one-month for twenty consecutive trading days. Fourth, the open price ranges between $2 and $8.

If the requirements of stationary price, declining volume and price range are full filled in any trading day during the sample period, it is regarded as a trading signal. In compliance with the trading signal, there are 434 stocks selected from the sample pool; all of these stocks could be the possible rotation targets of hedge initiators.

1.2. Selection criteria for sample stocks. As the possible hedging stocks are given above, the selection criteria for the sample stocks are as follows. First, the trading signal appears for five consecutive trading days and the open price on the fifth trading day is regarded as the holding cost. Second, the maximum return exceeds 20% in the one-month holding period. According to these criteria, we select 84 sample stocks in the sample period.

2. Methodology

We employ two GARCH models to examine the relationships of return-order imbalance and volatility-order imbalance.

We employ the following model to examine time varying return-order imbalance relation.

$$R_t = \alpha + \beta \times OI_t + \varepsilon_t,$$

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

$$h_t = A + B_1 \times h_{t-1} + C,$$

where R_t is the return in period t, defined as $\ln(P_t/P_{t-1})$, OI_t is the explanatory variable "Order Imbalance". β is the coefficient describing the impact of Order Imbalance on stock return. ε_t is the residual of the stock return in period t. h_t is the conditional variance in period t. Ω_{t-1} is the information set in period t-1.

We also examine volatility-order imbalance relation from the following model:

$$R_t = \alpha + \varepsilon_t,$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t), \quad (2)$$

$$h_t = A + B_1 \times h_{t-1} + C \times \varepsilon_{t-1}^2 + D,$$

where R_t is the return in period t, defined as $\ln(P_t/P_{t-1})$. OI_t is the explanatory variable "Order Imbalance". ε_t is the residual of the stock return in period t. h_t is the conditional variance in period t. Ω_{t-1} is the information set in period t-1. D represents the impact of the order imbalance on volatility of return. We expect a positive sign on this coefficient because large order imbalances are positively associated with large volatilities.

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 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

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

Definition 4: Feedback relationship, $x_1 <=> x_2$. There is a feedback relationship between x_1 and x_2 if

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

and

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

To explore the dynamic relationship of a bi-variate system, we form the five statistical hypotheses in 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, 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 hypothesis. 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 four testing sequences and six tests are summarized in a decision-tree flow chart in Figure 1.

Table 1. Hypotheses on the dynamic relationship of a bi-variate 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 $E(\underset{\sim}{\varepsilon_t} \varepsilon_{t+k}) = 0$, for $k \neq 0$ and $E(\underset{\sim}{\varepsilon_t} \varepsilon_{t+k}) = \Sigma$, for $k = 0$, where

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}.$$
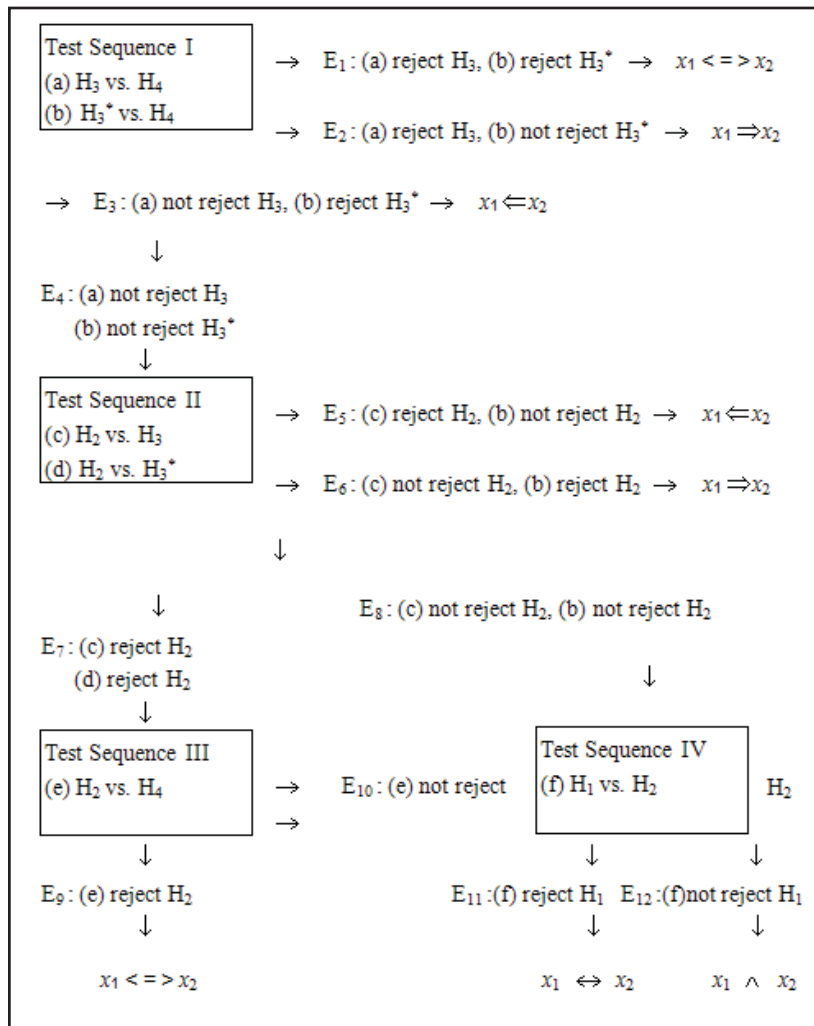
Fig. 1. Test flow chart of a multiple hypothesis testing procedure

3. Empirical results

3.1. Unconditional contemporaneous return – order imbalance relationship. We run a multiple-regression of returns on the most recent five lagged order imbalances to examine whether the previous order imbalances have influence on stock returns. Furthermore, in order to realize the convergence speed on market efficiency, we utilize different time interval lengths of 5 minutes, 10 minutes, and 15 minutes to see the effect of order imbalances on stock returns become smoothing out over time. Table 2 summarizes the significance of unconditional lagged effect.

To sum up, under the various time interval lengths of 5 minutes, 10 minutes, and 15 minutes, no more than 50% of the first lagged order imbalance has a positive influence on stock returns, and the significantly positive influences on stocks return of the first lagged order imbalance are 11.9%, 2.4% and 8.3% in 95% confidence level for the various time intervals respectively. The results are inconsistent with Chordia and Subrahmanyam (2004), who argued that lagged order imbalances, especially the first lagged order imbalance, are significantly positively related to the stock returns.

We also find that the number of significant lagged order imbalance decreases as time interval gets longer. This proves that the sophisticated investors react to the order imbalances by executing countervailing trades. In other words, countervailing trades help improve the efficiency of the market.

Table 2. Significance of unconditional lagged order imbalance-return relation

Panel A. Five minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
OI_{t-1}	50.0%	11.9%	4.8%
OI_{t-2}	34.5%	2.4%	10.7%
OI_{t-3}	50.0%	8.3%	1.2%
OI_{t-4}	50.0%	6.0%	3.6%
OI_{t-5}	41.7%	4.8%	4.8%
Panel B. Ten minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
OI_{t-1}	42.9%	4.8%	7.1%
OI_{t-2}	52.4%	4.8%	2.4%
OI_{t-3}	42.9%	3.6%	4.8%
OI_{t-4}	41.7%	2.4%	4.8%
OI_{t-5}	44.0%	1.2%	2.4%

Table 2 (cont.). Significance of unconditional lagged order imbalance-return relation

Panel C. Fifteen minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
OI_{t-1}	44.0%	3.6%	2.4%
OI_{t-2}	35.7%	0.0%	4.8%
OI_{t-3}	44.0%	1.2%	2.4%
OI_{t-4}	41.7%	2.4%	1.2%
OI_{t-5}	35.7%	2.4%	1.2%

3.2. Conditional contemporaneous return – order imbalance relationship. The multiple-regression model presented above showed that lagged order imbalances have no significant influence on current stock returns. This means we would be hard-pressed to come up with a profitable trading strategy based on lagged order imbalances alone. In this section, we incorporate the contemporaneous order imbalances into the multiple-regression model as explanatory variables. Table 3 summarizes the significance of contemporaneous effect.

We find that in this updated model, contemporaneous order imbalances actually play a central role in explaining the stock returns in all time intervals. In 95% confidence level, more than 80% of the contemporaneous order imbalances have positive influences on stock returns, and at least 45% are significantly positive in all time intervals. In addition, we also find that more than 50% of the lagged one order imbalances have a negative impact on current stock returns. The result is inconsistent with Chordia and Subrahmanyam (2004), which asserted that the current imbalance is positive and significant for virtually all the firms. Whereas the average coefficients on the lagged imbalances are negative and significant, and about 80% of the coefficients on these imbalances are negative, with about 30% being negative and significant.

The possible explanations are as follows. First, the market maker raised the bid-ask quote appropriately when the large order imbalance appeared so they would not need to decrease the bid-ask quote in the following period correspondingly. Second, if market maker did not have enough inventories for trade, they would be inclined to maintain a higher bid-ask quote because they fear that the informed traders will continue buying the stock at a lower price.

Finally, we find that the percentage of significantly positive influence of contemporaneous order imbalances on stock returns declines from 66.7% to 47.6% in 95% confidence level as the trading interval goes from five to fifteen minutes. On the other hand, the improving of market efficiency seems to exist as the time interval increases.

Table 3. Significance of contemporaneous return-order imbalance relation

Panel A. Five minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
OI_t	89.3%	66.7%	6.0%
OI_{t-1}	42.9%	6.0%	9.5%
OI_{t-2}	38.1%	4.8%	10.7%
OI_{t-3}	47.6%	8.3%	7.1%
OI_{t-4}	50.0%	8.3%	3.6%
Panel B. Ten minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
OI_t	86.9%	56.0%	4.8%
OI_{t-1}	41.7%	7.1%	9.5%
OI_{t-2}	57.1%	10.7%	2.4%
OI_{t-3}	44.0%	2.4%	6.0%
OI_{t-4}	42.9%	4.8%	3.6%
Panel C. Fifteen minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
OI_t	88.1%	47.6%	4.8%
OI_{t-1}	46.4%	7.1%	8.3%
OI_{t-2}	45.2%	2.4%	2.4%
OI_{t-3}	47.6%	1.2%	2.4%
OI_{t-4}	51.2%	1.2%	0.0%

3.3. Relationship between returns and order imbalances. In the previous sections, we realized that the contemporaneous order imbalances actually have positive influences on current stock returns in multiple-regression model. However, in the multiple-regression model, the influences on stock returns are not completely explained by order imbalances alone but also by price volatility as well. In this section, we develop the GARCH (1,1) model to gauge the exact relationship between order imbalances and stock returns. We expect that the percentage of contemporaneous order imbalances having a significantly positive influence on current stock returns in GARCH (1,1) model should be less than it has in the multiple-regression model since the GARCH (1,1) model excludes from considering the price volatility, which, according to our reasoning, affects stock returns as well. Table 4 presents the result of GARCH (1,1) model.

Table 4. Significance of return-order imbalance relation in GARCH (1,1) model

Panel A. Five minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
$B(1)$	100.0%	98.8%	0.0%
β	83.3%	71.4%	10.7%
Panel B. Ten minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
$B(1)$	100.0%	76.2%	0.0%
β	71.4%	45.2%	7.1%

Table 4 (cont.). Significance of return-order imbalance relation in GARCH (1,1) model

Panel C. Fifteen minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
$B(1)$	100.0%	50.0%	0.0%
β	63.1%	26.2%	6.0%

According to our results, the percentage of contemporaneous order imbalances having a significantly positive influence on current stock returns decreased from 71.4% to 26.2% as the time interval increased at the 95% confidence interval. The results suggest that as the time interval increased, the effect order imbalances has on stock returns gradually dies out, and the investors find it harder to profit only by observing the order imbalances. The situation provides powerful evidences that the market is getting more efficient as the time interval becomes longer.

Moreover, at the 95% confidence level, note that the percentage of positive and significant coefficients is 71.4% in GARCH model in five minutes interval, but it is only 66.7% in OLS model. This result is contrary to our expectation. One possible explanation is that investors pay more attention to order imbalances and disregard the risk as the stock price goes up in the very short term (e.g. five-minute interval). Hence, the volatility of price has less influence on stock returns in the shortest time interval.

3.4. Relationship between volatility and order imbalances. We would also like to know if the order imbalances have any influence on the volatility of stock returns. To that end, we develop another GARCH (1, 1) model, with the dependent variable being the volatility of stock returns and the independent variable being order imbalances. Table 5 summarizes the significant influence of order imbalances to volatility.

In general, order imbalances go hand in hand with large volatilities of stock returns. We would expect that there is a positive correlation between these two variables in our empirical results. However, the actual results are quite to the contrary. We find that nearly 50% of our data exhibit negative correlations between order imbalances and volatility. Furthermore, less than 11% actually show the significant influence on volatility either way at a 95% confidence level. Based on this result, it's very hard for us to specifically pin down the effect of order imbalances on return volatility.

We can attribute this unexpected result to the outstanding performance of the market makers. Since we know that the most important responsibility of market makers is to maintain the stability of stock prices, if market makers are smart enough to discover private information through order imbalance or are abundantly endowed in inventories and funds, they can control the price movements well and beat the informed traders and noise traders. In this case, the relationship between order imbalances and return volatility is insignificant.

Table 5. Significance of volatility-order imbalance relation in GARCH(1, 1) model

Panel A. Five minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
$B(1)$	100.0%	64.3%	0.0%
D	48.8%	13.1%	10.7%
Panel B. Ten minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
$B(1)$	100.0%	48.8%	0.0%
D	56.0%	9.5%	1.2%
Panel C. Fifteen minutes interval			
	Percent positive	Percent positive and significant	Percent negative and significant
$B(1)$	100.0%	35.7%	0.0%
D	51.2%	3.6%	3.6%

3.5. Trading strategy. In previous section, we described the selection criteria for the sample stocks. All the 84 sample companies have the same characteristics: stationary price, declining volume, and small price range. The sample date for each company's stocks is the day on which the highest price appears during the one-month holding period.

According to our empirical results in the previous section, we find that the contemporaneous order imbalances have significantly positive influence on stock returns, although the magnitude of this effect decreased as the time interval increased. In this section, we are interested in knowing whether an order imbalance-based trading strategy can beat the market or not. Furthermore, since we can expect the market to become more efficient, we can reasonably infer that the returns for shorter time intervals would be greater compared to that for longer time intervals. After all, investors will have a hard time going up against an efficient stock market.

The way an order imbalance-based trading strategy works is simple: long a stock when the order imbalance is positive, and sell it when the order imbalance becomes negative.

To examine the effectiveness of our trading strategy, we calculate the returns based on our strategy in two different ways, one with trading price and the other with the bid-ask price. The reason for calculating the returns in two different manners is that, while all of our empirical models utilized the transaction prices, the investors could only trade at the corresponding bid-ask prices. Furthermore, for each of the models, we also verify if it would be more

advantageous to focus only on the top 10% order imbalances by volume. That is, we propose a total of four models, with different prices used to calculate returns and different focus on order imbalances.

Table 6 presents the return pattern for the trading strategy with all order imbalances considered. In panel A, we find that the total returns based on transaction price are 157.82%, 103.74% and 65.41% with time intervals of 5, 10, and 15 minutes respectively. All of them exhibit significantly positive returns. Moreover, a point specifically worth noting is that, for the returns of the five-minute interval, the return generated by a trading strategy based on order imbalances alone actually outperforms the original return of 126.82%. However, the returns based on bid-ask price are -1528.39%, -928.58%, and -606.37% respectively for each time interval.

Table 6. Results of trading strategy

Panel A. Without truncated			
	Original return	Return of bid-ask price	Return of transaction price
5 minutes	126.82%	-1528.39%	157.82%
10 minutes	126.82%	-928.58%	103.74%
15 minutes	126.82%	-606.37%	65.41%
Panel B. Truncated 90%			
	original return	Return of bid ask price	Return of transaction price
5 minutes	126.82%	-77.59%	66.40%
10 minutes	126.82%	-79.21%	-5.90%
15 minutes	126.82%	-137.59%	-28.77%
Panel C. Paired sample test			
	Return of non-truncated	Return of truncated	T-stat of paired test
5 minutes	-0.1857	-0.0098	-5.7310
10 minutes	-0.1109	-0.0137	-5.5399
15 minutes	-0.0684	-0.0293	-2.7457

Apparently, the returns based on transaction price perform much better than the return based on bid-ask price. The major reason for this is that our sample stocks have higher bid-ask spread against general stocks. Because all of our sample stocks are potential "rotation" targets, or hedge stocks, their characteristics suggest that, since the majority of the outstanding shares are held by certain hedge initiators, the daily trading volume is quite small. In this case, the market makers tend to lower their inventories to conserve their funds for future trading purposes. This means that the market makers have much funds available but otherwise little inventory. At this moment, if buyers suddenly flood the market with large orders, the only way for market makers to resist these orders is to lower the bid price and raise the ask price.

In Panel B of Table 6, the total returns based on transaction price for the various time intervals are

66.4%, -5.9% and -28.77% respectively. On the other hand, the returns based on bid-ask price are -77.59%, -79.21%, and -137.59% respectively for each time interval. Since this pattern is similar to that observed in the previous section, it can be reasonably inferred that inventory cost also plays an important role in producing this return pattern.

We employ one-tail paired sample t-test to examine whether the truncated trading strategy could have better performance than the corresponding non-truncated trading strategy. Panel C of Table 6 summarizes the test results with various time intervals.

At the 95% confidence level, all the *t*-statistics are significant, and thus we could reject the null hypotheses at the 95% confidence level. Based on our results, we know that if the return is calculated by bid-ask price, then the truncated trading strategy outperforms its non-truncated counterpart.

3.6. Return-order imbalance causality relationship in explaining trading strategy. To tell a story behind our empirical results, 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 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 17.86% of the sample firms for the entire sample, while a unidirectional relationship from order imbalances to returns is 13.10%. The percentage of firms that fall into the independent category is 17.86%. Moreover, 45.24% of firms exhibit a contemporaneous relationship between returns and order imbalances. Finally, 5.95% 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 smaller than that from returns to order imbalances, suggesting that order imbalance is not a better indicator for predicting future returns. It is not 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; Su et al., 2008; Kim and Masulis, 2011, Huang and Tung, 2013). In addition, the percentage of firms exhibiting a contemporaneous relationship is about eight 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

Panel A. All size					
	$x_1 \wedge x_2$	$x_1 <\!\!-\!\!> x_2$	$x_1 \Longrightarrow x_2$	$x_1 \Longleftarrow x_2$	$x_1 <\!\!=\!\!> x_2$
All trade size	17.86%	45.24%	17.86%	13.10%	5.95%
Panel B. Firm size					
	$x_1 \wedge x_2$	$x_1 <\!\!-\!\!> x_2$	$x_1 \Longrightarrow x$	$x_1 \Longleftarrow x_2$	$x_1 <\!\!=\!\!> x_2$
Small firm size	10.71%	57.14%	7.14%	10.71%	14.29%
Medium firm size	28.57%	28.57%	28.57%	14.29%	0.00%
Large firm size	14.29%	50.00%	17.86%	14.29%	3.57%
Panel C. Turnover					
	$x_1 \wedge x_2$	$x_1 <\!\!-\!\!> x_2$	$x_1 \Longrightarrow x$	$x_1 \Longleftarrow x_2$	$x_1 <\!\!=\!\!> x_2$
Small turnover	14.29%	46.43%	21.43%	10.71%	7.14%
Medium turnover	10.71%	64.29%	7.14%	17.86%	0.00%
Large turnover	28.57%	25.00%	25.00%	10.71%	10.71%

In order to provide the evidence showing the impact on the relation between returns and order imbalances, in Panels B and C, we divide firms into three groups according to the firm size and turnover. 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 10.71% in the small firm size quartile, while the corresponding number is 14.29% 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. The results in Panel C indicate that the unidirectional relationship from order imbalances to returns is 10.71% in the small turnover quartile, while the corresponding number is 10.71% in the large turnover quartile during the entire sample period. The turnover-stratified results are not obvious.

Conclusions

Ever since the stock market was established in the 1793, the investors struggled to find a way to beat the market and get abnormal returns. Despite the *efficient market hypothesis*, which asserted only changes in fundamental factors, such as profits or dividends, may affect stock price, many previous researches have indicated there exists a relationship between trading volume and stock returns. In fact, the investors' behaviors are completely revealed through the return-volume pattern, implying that if we could decode the return-volume pattern, we can perhaps understand investors' rationales as well. In this study, we

examine some relationships between order imbalances and stock returns.

We find that the contemporaneous order imbalances have a positive correlation with current stock returns in multiple-regression models and in GARCH (1,1) models. This relationship implies that buyers' large orders could put pressure on the stock price to go up and thus result in positive returns.

Furthermore, the negative correlation between the lagged order imbalance and current stock returns is insignificant. One possible explanation is that market makers do not overreact to the contemporaneous order imbalances; as a result, they do not need to adjust the quote in the following period.

We also examine the convergence speed to market efficiency. We get similar results in the GARCH (1,1) model and contemporaneous multiple-regression model, which show that the percentage of order imbalances with a significantly positive return decreases as the time interval increases. This situation provides strong evidence that the market efficiency is improved by the presence of sophisticated investors who react to the order imbalances by executing countervailing trades, which is consistent with Chordia et al. (2005).

Moreover, we find that order imbalances do not have a significant influence on return volatility. One possible reason is that market makers keep the stock price relatively stable. This idea corresponds to our suggestion that market makers do not really overreact in response to order imbalances. This also explains why the lagged order imbalance has insignificant negative correlation with current stock returns.

Then, based on the finding that the contemporaneous order imbalances have significantly positive influence on stock returns, we develop an order imbalance-based trading strategy. We have reached two conclusions based on this simulated strategy. First, the truncated trading strategy performs much better than its non-truncated counterpart. Second, return from the truncated trading strategy decreases when the time interval increases. This corresponds to the idea that market efficiency can be improved by the presence of countervailing trades.

In this study, we demonstrate evidence about market efficiency and the relationship between order imbalances and stock returns. Nonetheless, return of trading strategy apparently is worse than return of the market.

Since we only trade at the end of time interval, we could miss out on many advantageous trading opportunities within each time interval. The effect of various trading time within each respective time intervals on returns is left for future research.

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