International Journal of Economics and Financial Issues
Vol. 3, No. 3, 2013, pp.591-601
ISSN: 2146-4138
www.econjournals.com

Speed of Convergence to Market Efficiency: Example of Top loser Stocks

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ABSTRACT: This study investigates the convergence process toward efficiency of daily top losers. We find that significance of order imbalance coefficients decreases with increasing time interval, indicating evidences on convergence to market efficiency. A time-varying GARCH model is employed to examine the relation between order imbalance and volatility. The significance of order imbalance coefficients shows a decay pattern, which also supports convergence to market efficiency. We develop an imbalance-based trading strategy and can not make profits from these daily top losers under bid/ask price. A nested causality approach, which examines dynamic return-order imbalance relation during price formation process, confirms the results.

Keywords: Market efficiency; order imbalance; top losers; volatility
JEL Classifications: G12; G14

1. Introduction

Market efficiency has drawn much attention in finance field, which was defined by Fama (1970). Market efficiency suggests that at any given time, prices fully reflect all available information on a particular stock or market (e.g. Dicle et al., 2010). Following this concept, no investor has a privilege in predicting return because no one has access to information not already available to everyone else. However, researchers have compiled a long list of empirical anomalies in the real world. (Durham, 2001; Hsieh and Walkling, 2006; Huang and Wang, 2009)

For decades, price movement is a central issue for many scholars, and much research has been devoted to finding the relation between return and trading volume. Chordia et al. (2002) documented a seemingly related and intriguing phenomenon in their study of market-wide order imbalances on the New York Stock Exchange. The market order imbalance, define as aggregated daily market purchase orders less sell order for stocks in the S&P500 index, is highly predictable from day-to-day. A day with a high imbalance on the buy side will likely be followed by several additional days of aggregate buy-side imbalances; and similarly for an initial imbalance on the sell side. This implies that investors continue buying or selling for quite a long time, either because they are herding (Hirshleifer et al., 1994), or because they are splitting large orders across days (Kyle, 1985), or both. In addition, Chordia and Subrahmanyam (2004) studied on the relation between order imbalance and daily return of individual stock. Price pressures caused by auto-correlated imbalances cause a positive relation between lagged imbalances and returns, which reverses sign after controlling for the current imbalance.

Moreover, based on individual stock, Chordia et al. (2005) present how the market converges to efficiency. Market makers change quotes away from fundamental value to react to order imbalances in an effort to control inventory.

Meanwhile, some investors conduct countervailing trades in the opposite direction to arbitrage. This arbitrage activity takes at least a few minutes since arbitragers must ascertain whether or not there is new relevant information about values. Chordia et al. (2005) have examined the process of which market converge to efficiency based on the data of NYSE large firms. They find that it takes more than five minutes but less than sixty minutes for the market to achieve weak-form efficiency.[1]

Compared with Chordia et al. (2005), we narrow the range of our research to daily top losers, which play an important role in market efficiency since these stocks announce extremely valuable information to the general public. Following Chordia et al. (2005), we use intraday data (5-, 10-, and 15-min time intervals) to examine not only the impact of discretionary traders on return but also the impact of discretionary traders on volatility and especially the according responses from uninformed market makers who have the responsibility to reduce volatility.

We first examine both contemporaneous and lagged relations between returns and order imbalances. The empirical results show that lagged imbalances are positively related to returns. In particular, about 77% of the coefficients on the first lag of order imbalances are positive, and more than a quarter are positive and significant. Our empirical results also indicated that the current imbalances are positive and significant for virtually all the firms. The contemporaneous relation between imbalances and returns is consistent with both inventory and asymmetric information effects of price formation.

We then use a time varying GARCH (1,1) model to investigate the relation between volatilities and order imbalances. We expected a positive order imbalance accompanied by a large volatility on stock price. The empirical results show that about half of significant coefficients are positively associated between volatility and order imbalance. We have two stories to explain the finding. First, the evidence implies that market makers have good ability to control the volatility of stock price, and using the bid-ask spread to adjust the stock price fluctuation in the market. Second, market makers pay their attention on the "stability of the market" more than on the "rate of return".

Moreover, our empirical findings show a clear pattern on convergence to market efficiency. We document a declining trend of the significant coefficients in longer time interval. The results suggest that the order imbalance still have strong influence on volatility in the short time, while market makers reduce the influence in longer period of time.

Finally, we manage to develop an imbalance-based trading strategy for top losers. In order to tell a story behind the profitability of order imbalance based trading strategy, our empirical findings indicate that the unidirectional relationship from order imbalances to returns is 13.04% in the small firm size quartile, while the corresponding number is 17.39% 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.

Our contributions are as follows. First, we indicate that the direct relation between order imbalance and return should consider the linkage from volatility. Second, market maker behaviors play a very important role in mitigating volatility from discretionary trades through inventory adjustments.

The rest of this study is organized as follow. Section II is data and section III is methodology. Our empirical results are shown in section IV. Section V concludes.

[1] Chordia et al. (2005) report there is little evidence of unconditional serial dependence on returns for no t-statistic exceeds 2.0 in absolute value and thirteen of the fifteen are less than 1.0 in absolute value. This suggests that these stocks conform well to weak-form efficiency; i.e., using only the past history of returns, there is little, if any, predictability of future returns even over intervals as short as five minutes.

2. Data

Since we already know that serial dependence in return is close to zero for active stock over a daily horizon, our investigation of the efficiency-creating process focus on intra-day trading. Data sources were from the Center for Research in Security Prices (CRSP) and the NYSE Trades and Automated Quotations (TAQ) databases. First, we screen daily return to find daily top losers from July, 2006 to December, 2006. The definition of top loser in this study is the stock which had the worst daily open-to-close return (closing price minus opening price divided by opening price). We collected seventy stocks in our sample. Then, we collected the corresponding intraday data in TAQ database for these 70 samples. Following Lee and Ready (1991), any quote less than five seconds prior to the trade was ignored and the first one at least five seconds prior to the trade was retained. If a transaction occurs above the prevailing quote mid-point, it is regarded as a buyer-initiated order and vice versa. If a transaction occurs exactly at the mid-point, it is signed from tick test.

The untabluated results present the mean value of market capitalization is 135 million, and the median is 48 million. The average trading volume is 5,311 thousand, and the median is 1,524 thousand. Both the market capitalization and the trading volume have outliers. It self-explains that medians are much smaller than means, and both of them are positive skew. In addition, the mean value of the daily return is -28.53% in our 70 samples. We find that 60% of market capitalizations are under 100 million.

3. Methodology

We employed two different approaches to examine return-order imbalance and volatility-order imbalance. First, we examine whether lagged order imbalances have predictability for current stock return.

$$R_t = \alpha + \beta_1 OI_{t-1} + \beta_2 OI_{t-2} + \beta_3 OI_{t-3} + \beta_4 OI_{t-4} + \beta_5 OI_{t-5} + \varepsilon_t \qquad (1)$$

where R_t is the stock return in period t, defined as $(P_t- P_{t-1})/P_{t-1,}$ $OI_{t,}$ are lagged order imbalance at time t of the stock.

We expected a positive return-lagged imbalance. Since market makers are risk averse, an imbalance creates price pressure from inventory change. However, since liquidity demands are auto-correlated, there is further contemporaneous price pressure that is correlated with the lagged price pressure. This leads to a positive predictive relation between lagged imbalance and future price movements. In addition, if the relations were significant, we could develop a trading strategy.

Furthermore, we included the contemporaneous imbalance and four lags of order imbalance. Conditional on current imbalance, we investigate current return and lagged order imbalance relation.

$$R_t = \alpha + \beta_1 OI_t + \beta_2 OI_{t-1} + \beta_3 OI_{t-2} + \beta_4 OI_{t-3} + \beta_5 OI_{t-4} + \varepsilon_t \qquad (2)$$

where R_t is the stock return in period t, defined as $(P_t- P_{t-1})/P_{t-1,}$ OI_t are order imbalance at time t of the stock.

We expected a positive coefficient of current imbalances and negative signs in return-lagged imbalances relations, after controlling current imbalance.

In order to make sure that return-order imbalance relation from regression is not from associated risk increase, we employ a time varying GARCH (1,1) model to examine time varying return-order imbalance.

$$R_t = \alpha + \beta \times OI_t + \varepsilon_t \qquad \varepsilon_t \mid \Omega_{t-1} \sim N(0,h_t) \qquad (3)$$
$$h_t = A_1 + B_1 h_{t-1} + C_1 \varepsilon^2_{t-1}$$

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

The β coefficient represents whether the order imbalance volumes have significant influence on the stock returns. We are also interested in examining dynamic relation between volatility and order imbalance. Intuitively, we expected that high order imbalances are accompanied by large volatilities.

$$R_t = \alpha + \varepsilon_t \qquad \varepsilon_t \mid \Omega_{t-1} \sim N(0,h_t) \qquad (4)$$
$$h_t = A_1 + B_1 h_{t-1} + C_1 \varepsilon^2_{t-1} + D_1 OI_t$$

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

In order to explain the story behind order imbalance based trading strategy developed from our empirical results, we employ a nested causality approach 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

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) = Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}, \underset{\sim}{x_{2(T+1)}}) \tag{5}$$

and

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

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

x_1 and x_2 are contemporaneously related if

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

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

and

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) = Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) \tag{9}$$

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

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

There is a unidirectional relationship from x_1 to x_2 if

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

and

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

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

There is a feedback relationship between x_1 and x_2 if

$$Var(x_{1(T+1)} \mid \underset{\sim}{x_1}) > Var(x_{1(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) \tag{13}$$

and

$$Var(x_{2(T+1)} \mid \underset{\sim}{x_2}) > Var(x_{2(T+1)} \mid \underset{\sim}{x_1}, \underset{\sim}{x_2}) \tag{14}$$

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, 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. 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.

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.

Table 1. Hypotheses on the Dynamic Relationship of a Bivariate System

Hypotheses	The VAR test
$H_1 : x_1 \wedge x_2$	φ_{12} (L)= φ_{21} (L)=0 , andσ_{12}=σ_{21} =0
$H_2 : x_1 <-> x_2$	φ_{12} (L)= φ_{21} (L)=0
$H_3 : x_1 \neq> x_2$	φ_{21} (L)=0
$H_3^* : x_2 \neq> x_1$	φ_{12} (L)=0
$H_4 : x_1 <=> x_2$	φ_{12} (L)* φ_{21} (L) $\neq$0
$H_5 : x_1 \neq>> x_2$	φ_{21} (L)=0 , andσ_{12}=σ_{21} =0
$H_6 : x_2 \neq>> x_1$	φ_{12} (L)=0 , andσ_{12}=σ_{21} =0
$H_7 : x_1 <<=>> x_2$	φ_{12} (L)* φ_{21} (L) $\neq$0 , andσ_{12}=σ_{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*≠*0* and $E(\underset{\sim}{\varepsilon_t}\, \underset{\sim}{\varepsilon_{t+k}}) = \Sigma$ for *k*=0, where $\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$

Note: 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 whereσ_{12}=σ_{21} =0 ; and $<<=>>$ is a strong feedback relationship whereσ_{12}=σ_{21} =0

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,

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.

Test Sequence I		
(a) H_3 vs. H_4	→	E_1 : (a) reject H_3, (b) reject H_3^* → $x_1 <=> x_2$
(b) H_3^* vs. H_4	→	E_2 : (a) reject H_3, (b) not reject H_3^* → $x_1 \Rightarrow x_2$
	→	E_3 : (a) not reject H_3, (b) reject H_3^* → $x_1 \Leftarrow x_2$

↓

E_4 : (a) not reject H_3
(b) not reject H_3^*
$\downarrow$

Test Sequence II (c) H_2 vs. H_3 (d) H_2 vs. H_3^*	$\rightarrow$ E_5 :(c) reject H_2, (b) not reject H_2 $\rightarrow$ $x_1 \Leftarrow x_2$ $\rightarrow$ E_6 : (c) not reject H_2, (b) reject H_2 $\rightarrow$ $x_1 \Rightarrow x_2$

$\downarrow$ E_7 : (c) reject H_2
(d) reject H_2
$\downarrow$

$\downarrow$ E_8 :(c) not reject H_2, (b) not reject H_2
$\downarrow$

Test Sequence III (e) H_2 vs. H_4	$\rightarrow$ E_{10} : (e) not reject H_2 $\rightarrow$	Test Sequence IV (f) H_1 vs. H_2

$\downarrow$ E_9 : (e) reject H_2 $\downarrow$ $x_1 <=> x_2$

$\downarrow$ E_{11} :(f) reject H_1 $\downarrow$ $x_1 \leftrightarrow x_2$

$\downarrow$ E_{12} :(f)not reject H_1 $\downarrow$ $x_1 \wedge x_2$

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 Step 4. 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.

4. Empirical results

4.1 Unconditional lagged return-order imbalance relation

Table 3 represents the results of relation between returns and lagged order imbalance in 5, 10 and 15 minutes time intervals. Under 5% significance level, the percentages of significantly positive coefficients on the first lag order imbalances are 11%, 9%, and 9% in 5, 10, and 15 minutes respectively, which are larger than the percentages of negative and significant coefficients, 7%, 9%, and 6%. These results are in accordance with daily findings in Chordia and Subrahmanyam (2004). In particular, about 77% of the coefficients on the first lag of order imbalances are positive, and more than a quarter are significantly positive.

Table 3. Significance test results of unconditional order imbalance regressions - lagged 1 through lagged 5

	Positive and significant			Negative and significant		
	5-min	**10-min**	**15-min**	**5-min**	**10-min**	**15-min**
OI_{t-1}	11%	9%	9%	7%	9%	6%
OI_{t-2}	10%	7%	4%	11%	11%	7%
OI_{t-3}	4%	6%	1%	3%	7%	6%
OI_{t-4}	9%	3%	1%	4%	10%	6%
OI_{t-5}	4%	1%	3%	9%	6%	7%

$R_t=\alpha_0 + \alpha_1 OI_{t-1}+\alpha_2 OI_{t-2}+\alpha_3 OI_{t-3}+\alpha_4 OI_{t-4}+\alpha_5 OI_{t-5}+\varepsilon_t$,
where R_t is the current stock return of the individual stock, and OI_{t-i}, where i=1, 2, 3, 4, and 5, are lagged order imbalances at time t-1, t-2, t-3, t-4, and t-5 for each individual stock, ε_t is the residual of the current stock return. "Significant" denotes significance at the 5% level.

However, our significant test results are inconsistent with their findings. The possible reason is either that our intraday time interval is too short to reveal information timely or that the market is efficient enough to reflect all information. We believe that market makers do not have great price pressures in handling top losers. Apparently, liquidity traders are eager to dump their holdings to market makers.

In convergence speed, we find that percentage of significantly positive at short time interval is much larger than those at long time intervals. Our results are consistent with the findings of Chordia, et al. (2005). Obviously, at three significant levels, order imbalances have the declining predictive ability on returns as the time interval increases.

4.2 Conditional contemporaneous return–order imbalance relation

Table 4 represents the results of significant test between contemporaneous returns and order imbalances in t5, 10 and 15 minutes time intervals. Coefficients of current return and the contemporaneous order imbalance are 63%, 47%, and 41% positive and significant in 5 minutes, 10 minutes, and 15 minutes respectively. These results are also consistent with the findings of Chordia and Subrahmanyam (2004). The contemporaneous relation between imbalances and returns is consistent with both inventory and asymmetric information effects of price formation.

In convergence, a decreasing trend, 63%, 47%, and 41% in 5, 10, and 15 minutes respectively, has been shown. It implies that the relation between current return and order imbalance is more obvious in short reactive time than in longer time intervals. Furthermore, Chordia and Subrahmanyam (2004) also mentioned that after controlling for the current imbalance, lagged imbalances are negatively related to current price movements. They argued that predictability of lagged imbalance on future return disappears after controlling for the current order imbalance. However, our empirical results show a different picture. Table 4 shows that percentage in negative and significant coefficients of lagged 1 period imbalances are only 9%, 9%, and 13% in 5, 10, and 15 minutes respectively. A possible explanation is that coefficient on the lagged imbalance reverse sign in the presence of the contemporaneous imbalance only when imbalances are auto-correlated.

Table 4 Significance test results of conditional order imbalance regressions - lagged 0 through lagged 4

	Positive and significant			Negative and significant		
	5-min	**10-min**	**15-min**	**5-min**	**10-min**	**15-min**
OI_t	63%	47%	41%	3%	4%	1%
OI_{t-1}	10%	7%	6%	9%	9%	13%
OI_{t-2}	10%	4%	6%	10%	11%	9%
OI_{t-3}	4%	6%	4%	6%	10%	9%
OI_{t-4}	9%	1%	3%	4%	9%	3%

$R_t=\alpha_0 + \alpha_1 OI_t+\alpha_2 OI_{t-1}+\alpha_3 OI_{t-2}+\alpha_4 OI_{t-3}+\alpha_5 OI_{t-4}+\varepsilon_t$

where R_t is the current stock return of the individual stock at time t. OI_{t-i}, where i=0, 1, 2, 3, and 4, represents the contemporaneous order imbalances at time t and the lagged order imbalances at time t-1, t-2, t-3, and t-4, for each individual stock. ε_t is the residual of the current stock return. "Significant" denotes significance at the 5% level.

4.3 Dynamic relation between order imbalance and return

Panel A of Table 5 summarizes the results of dynamic return-order imbalance relation. It shows that positive coefficients of contemporaneous return and order imbalance for 5, 10 and 15 min horizons are 66%, 63% and 64% respectively; those with positive and significant coefficients for 5, 10 and 15-min time intervals are 46%, 40% and 21% respectively at 5% significant level. It implies that order imbalance is an explanatory variable for stock return even in a time varying model. Again, a declining trend in the percentage of significantly positive coefficients implies that market becomes more efficient in longer horizons.

4.4 Dynamic relation between order imbalance and volatility

We are also interested in examining the relations between volatilities and order imbalances and the expected sign is positive. The empirical results are exhibited in Panel B of Table 5. The significant coefficients in total samples are 24%, 12%, and 8% in 5-, 10-, and 15-min intervals respectively at the 5% significant level. Meanwhile, about half of those significant coefficients are positive relations between volatilities and order imbalances, which imply that market makers have good ability to control the volatility of stock price, and using the bid-ask spread to adjust the stock price fluctuation in the market.

Moreover, Panel B of Table 5 also demonstrates a declining trend of the significant coefficients in longer time interval is found. The results suggest that the order imbalance still have strong influence on volatility in the short time, while market makers try to reduce it.

4.5 Trading strategy based on return-order imbalance relation

Given the evidence of the return predictability from order imbalances in previous sections, we try to develop an order imbalance based trading strategy. Average return from buy-and-hold of our 70 top losers is -28.53%. We formed our imbalance-based trading strategy, which is to short sell when negative order imbalance appears and to buy back when positive order imbalance. We ignore transaction costs and taxes. This trading strategy is based on 2 scenarios – no truncation and 90% truncation.

The trading results are exhibited in Table 6. In Panel A, we use trading prices. Mean of no truncated return are 9.16%, 9.9%, and 10.35% in 5-, 10-, 15-min respectively. Average return of 90% truncation are 5.86%, 1.14%, and 4.14% in 5-, 10-, 15-min respectively. It implies that our order imbalance based trading strategy beats return of buy and hold. In Panel B of Table 6, the rates of return were calculated by buying stocks at ask price and selling stocks at bid price. We find that all returns of strategies in Panel B are smaller than those in Panel A. In Panel B, mean of no truncated return are -24.91%, -9.93%, and -6.57% in 5-, 10-, 15-min respectively. Average return of 90% truncation are -1.30%, -5.04%, and -1.13% in 5-, 10-, 15-min respectively.

Table 5. The significant test of contemporaneous return (Volatility) - order imbalance relation in GARCH (1,1)

Panel A Dynamic Return-Order Imbalance GARCH(1,1) Relation

$R_t = \alpha + \beta * OI_t + \varepsilon_t, \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t), h_t = A + Bh_{t-1} + C\varepsilon_{t-1}^2$

where R_t is the return in period t, and is defined as $\ln(P_t/P_{t-1})$, OI_t is the explanatory variable, the order imbalance, β is the coefficient describing the impact of the order imbalance on stock returns, ε_t is the residual value of the stock return in period t, Ω_{t-1} is the information set in period t-1, and α, A, B, and C are intercepts and coefficients. "Significant" denotes significance at the 5% level.

	Percent Positive	Percent Positive and Significant	Percent Negative and Significant
5-min interval	66%	46%	4%
10-min interval	63%	40%	5%
15-min interval	64%	21%	9%

Panel B Dynamic Volatility-Order Imbalance GARCH(1,1) Relation

$R_t = \alpha + \varepsilon_t, \ \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t), h_t = A + Bh_{t-1} + C\varepsilon_{t-1}^2 + \gamma * OI_t$

where R_t is the return in period t, and is defined as $\ln(P_t/P_{t-1})$, OI_t is the explanatory variable, order imbalance, γis the coefficient describing the impact of order imbalance on stock volatility, ε_t is the residual value of the stock return in period t, Ω_{t-1} is the information set in period t-1, and α, A, B, C are intercepts and coefficients. "Significant" denotes significant at the 5% level.

	Percent Positive	Percent Positive and Significant	Percent Negative and Significant
5-min interval	47%	12%	12%
10-min interval	42%	6%	6%
15-min interval	52%	6%	2%

We use the matched-pairs t-test to examine whether order imbalance truncation trading strategy outperforms no truncation trading strategy. In untabulated report, we reject the null hypothesis. It implies that 90%-truncated trading strategy outperforms no-truncated one when the rates of return were calculated by buying stocks at ask price and selling stocks at bid price.

4.6 Dynamic 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 11.43% of the sample firms for the entire sample, while a unidirectional relationship from order imbalances to returns is 12.86%. The percentage of firms that fall into the independent category is 20.00%. Moreover, 48.57% of firms exhibit a contemporaneous relationship between returns and order imbalances. Finally, 7.14% 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 (Chordia and Subrahmanyam, 2004). In addition, the percentage of firms exhibiting a contemporaneous relationship is about seven 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 6. Results of return from speculative trading strategy

We formed our imbalance-based trading strategy, which is to short sell when negative order imbalance appears and to buy back when positive order imbalance. We ignore transaction costs and taxes. This trading strategy is based on 2 scenarios – no truncation and 90% truncation. In Panel A, we use trading prices. In Panel B, the rates of return were calculated by buying stocks at ask price and selling stocks at bid price.

Panel A. Daily return and the return from strategy under 0% and 90% OI truncated in each sample stocks– using trading price

	no truncated	90% truncated
Daily return	-28.53%	
5-min Return of strategy	9.16%	5.86%
10-min Return of strategy	9.90%	1.14%
15-min Return of strategy	10.35%	4.14%

Panel B. Daily return and the return from strategy under 0% and 90% OI truncated in each sample stocks– using bid/ask price

	no truncated	90% truncated
Daily return	-28.53%	
5-min Return of strategy	-24.91%	-1.30%
10-min Return of strategy	-9.93%	-5.04%
15-min Return of strategy	-6.47%	-1.13%

Table 7. Dynamic Nested Causality Relationship between Returns and Order Imbalances (in percentage)

	$x_1 \wedge x_2$	$x_1 <-> x_2$	$x_1 \Rightarrow x_2$	$x_1 \Leftarrow x_2$	$x_1 <=> x_2$
Panel A: All size					
All Trade Size	20.00	48.57	11.43	12.86	7.14
Panel B: Firm size					
Small Firm Size	21.74	43.48	13.04	13.04	8.70
Medium Firm Size	12.50	54.17	16.67	8.33	8.33
Large Firm Size	26.09	47.83	4.35	17.39	4.35
Panel C: Turnover					
Small Turnover	17.39	56.52	8.70	17.39	0.00
Medium Turnover	20.83	41.67	16.67	12.50	8.33
Large Turnover	21.74	47.83	8.70	8.70	13.04

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

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 (daily trading volume/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 13.04% in the small firm size quartile, while the corresponding number is 17.39% 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 17.39% in the small turnover quartile, while the corresponding number is 8.70% in the large turnover quartile during the entire sample period. The turnover-stratified results can be explained as follows. When the turnover is smaller, 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 small turnover quartile.

5. Conclusions

In efficient market hypothesis, it was generally believed that securities markets were extremely efficient in reflecting information about individual stocks and stock market as a whole. The story is that when information arises, news spreads very quickly and is incorporated into the prices of securities simultaneously. However, markets do not reach efficiency instantaneously, convergence is a necessity. There must need some time for the stock to converge to efficiency. The central purpose of our study is to investigate the convergence process toward efficiency of daily top losers in the stock market.

We divided the market behavior into the following three steps: Order imbalances in the first instance arise from traders who demand immediacy for liquidity or informational needs. Order imbalances are positively auto-correlated, which suggests that traders are herding, or spreading their orders out over time, or both. Second, market makers react to initial order imbalances by altering quotes away from fundamental value in an effort to control inventory. Finally, outside arbitrageurs intervene to add market-making capacity by conducting countervailing trades in the direction opposite to the initial order imbalances. This arbitrage activity takes at least a few minutes.

By selecting 70 samples of daily top losers, we first examined the relations between returns and order imbalances. We found that both in OLS method and GARCH model the significance of order imbalance coefficients decreased with increasing time interval (5, 10 and 15-min), indicating that our findings were in agreement with the convergence process to market efficiency mentioned above.

Second, we used GARCH model to test the relations between order imbalances and volatilities. Again, the significant coefficients had a declining pattern which also supported the convergence to market efficiency.

Third, we developed an imbalance-based trading strategy and made profit from these daily top losers. Our strategy was to short sell when seeing the first seller-initiated order imbalance and immediately buy back the underlying when the order imbalance transfer to buyer-initiated. We applied many methods in testing our strategy, such as using trading price or bid-ask price to evaluate the performance of the strategy, and selecting order imbalance with 0% or 90% truncation. All of them outperform buy and hold rate of return. Besides, the matched-pairs t-test showed that the average return of 90% truncated strategy was significant superior to that of no truncation in using bid-ask quote price.

Finally, according to our investigation of 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 large firm size quartile.

This study could extend to other corporate announcement events such as seasoned equity offering, and repurchases. In addition, Barclay and Warner (1993) and Anand and Chakravarty (2007) find that most of the cumulative stock price change is due to medium-size trades. Therefore, if we focus on medium-size trades, the convergence process should be quicker than that on all-size trades.

References

Anand, A., Chakravarty, S. (2007), *Stealth trading in options markets.* Journal of Financial and Quantitative Analysis, 42(1), 167-188.

Barclay, M.J., Warner, J.B. (1993), *Stealth trading and volatility: Which trades move prices?* Journal of Financial Economics, 34(3), 281-305.

Chen, C., Wu, C. (1999), *The dynamics of dividends, earnings and prices: Evidence and implications for dividend smoothing and signaling*. Journal of Empirical Finance, 6(1), 29-58.

Chordia, T., Roll, R., Subrahmanyam, A. (2002), *Order imbalance, liquidity, and market returns*. Journal of Financial Economics, 65(1), 111-130.

Chordia, T., Roll, R., Subrahmanyam, A. (2005), *Evidence on the speed of convergence to market efficiency.* Journal of Financial Economics, 76(2), 271-292.

Chordia, T., Subrahmanyam, A. (2004), *Order imbalance and individual stock returns: Theory and evidence*. Journal of Financial Economics, 72(3), 485-518.

Dicle, M., Beyhan, A., Yao, L. (2010), *Market efficiency and international diversification: Evidence from India.* International Review of Economics and Finance, 19(2), 313-339.

Durham, J.B. (2001), *Sensitivity analyses of anomalies in developed stock markets.* Journal of Banking and Finance, 25(8), 1503-1541.

Fama, E.F. (1970), *Efficient capital markets: A review of theory and empirical work.* Journal of Finance, 25(2), 383-417.

Hirshleifer, D., Subrahmanyam, A., Titman, S. (1994), *Security analysis and trading patterns when some investors receive information before others.* Journal of Finance, 49(5), 1665-1698.

Hsieh, J., Walkling, R.A. (2006), *The history and performance of concept stocks.* Journal of Banking and Finance, 30(9), 2433-2469.

Huang, D., Wang, F. (2009), *Cash, investments and asset returns*. Journal of Banking and Finance, 33(12), 2301-2311.

Kyle, A.S. (1985), *Continuous auctions and insider trading.* Econometrica, 53(6), 1315-1335.

Lee, C., Ready, M. (1991), *Inferring trade direction from intraday data.* Journal of Finance, 46(2), 733-747.