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International investment bank spillover efficiency in financial crisis

Abstract

The paper investigates convergence toward efficiency on international investment banks during financial crisis of 2008. First, the authors find that a conditional contemporaneous without reversal of lagged return-order imbalance relation, which are inconsistent with Chordia and Subrahmanyam (2004). It implies a different market behavior in financial crisis. The authors confirm the convergence process toward efficiency with a time varying GARCH model. In order to explore direct impact of order imbalance on volatility, the authors employ a GARCH model to examine volatility-imbalance relation. The results present that a negative volatility-imbalance relation and the impact of imbalances on volatility fades away within 15 minutes, which suggests that market makers have the capability to mitigate market volatility even in the financial turbulence. They make a further step to develop an imbalance based trading strategy to test market efficiency. The performances fail to beat the market during the crisis.

Keywords: order imbalance, market efficiency, causality relationship, investment bank, financial crisis.

JEL Classification: G10, G14, G21.

Introduction

Ever since Fama (1970) published his profound “Efficient Capital Markets” in his seminal review, the concept of market efficiency attracted much interest from various researchers. However, it has been suggested in the academic field that market is not perfectly efficient as proposed by Fama (1970). In particular, trading volume has provided the link between trading activity and returns. There are many different measures of trading volume, including number of trades, shares traded, and dollar amount of shares traded. Nonetheless, these measures can be high either due to a predominance of buyer-initiated or seller-initiated trades, or only because there’s large interest in trading, with equal amount of buy and sell trades. On the other hand, order imbalance, a method which classifies a trade as buyer (seller)-initiated by Lee and Ready (1991) algorithm and calculates the net direction during a specified period, takes account of the specific impact posed by buyer or seller, and thus can provide additional power in explaining stock returns, as noted by Chordia and Subrahmanyam (2004) and Su et al. (2012).

The financial crisis originated from the defaults of subprime mortgages starting in 2007. After the defaults, there were the breakouts of a series of liquidity problems faced by the issuers of related structured products. Liquidity problems then converted to panics among investors. The crisis went to its climax when Lehman Brothers filed bankruptcy on September, 15, 2008, and the market dropped hugely thereafter. Within two months, S&P 500 index slumped 28.1% and Dow Jones Industrialized Average index declined 21.3% as well. During the crisis, many financial service companies faced serious liquidity problems and resorted to governments for rescue, or even went bankruptcy. Fahlen-

brach et al. (2012) find that banks that relied more on short-term funding, had more leverage, and grew more are more likely to be banks that performed poorly in both crises. Berger and Bouwman (2013) document that capital enhances the performance of medium and large banks primarily during banking crises. Among the financial companies, we are particularly interested in investment banks because many of them were the issuers or holders of structured products or important liquidity providers in the financial markets.

Price-volume relation has been a perennial issue in financial literatures. Llorente et al. (2002) show that returns generated by hedging trades tend to reverse themselves, while returns generated by speculative trades continue. Chordia et al. (2002) show that order imbalance increases following market declines and vice versa, which shows that investors are contrarian on aggregate. Chordia and Subrahmanyam (2004) find that price pressures caused by autocorrelated imbalances cause a positive relation between lagged imbalances and returns, which reverses sign after controlling for current imbalances. They also find that order imbalance-based trading strategy yield significant returns statistically. Chordia et al. (2005) document that from the pattern of intra-day serial dependence, it takes more than five minutes but less than 60 minutes to achieve weak-form efficiency. Andrade et al. (2008) find that the cross-stock price pressure is higher among stocks with more correlated cash flows than among stocks with less correlated cash flows. We focus on not only individual stock return-order imbalance, but also cross-stock relation proposed by Andrade et al. (2008).

In this study, we examine international investment bank spillover efficiency in financial crisis. First, we find that lagged order imbalance does not reverse when conditioning on current imbalances, which are inconsistent with Chordia and Subrahmanyam (2004). Based on a time varying GARCH model, we document that the relation between con-

temporaneous imbalances and returns is still positive, but there is a huge drop in the percentage of significant positive relation, which implies that during the crisis, volatility plays an important role in return-order imbalance relation. Our empirical results on volatility-imbalance are inconsistent with Su et al. (2010). We argue that either prospect theory (Kahneman and Tversky, 1979) or leverage effect (Christie, 1982) explain the negative volatility-imbalance in market turbulence.

Our study proceeds as follows. In section 1, we describe data and methodology. Section 2 presents our empirical results and trading strategies. The final section concludes the paper.

1. Data and methodology

In order to examine international investment bank efficiency during financial crisis, we choose leading US and international investment banks. There are seven investment banks selected in our sample, including Bank of America (Ticker: BAC), Citigroup (C), Goldman Sachs (GS), Morgan Stanley (MS), Deutsche Bank (DB), UBS AG (UBS), and Nomura Holdings (NMR). The former four are US investment banks, and the latter three are non-US investment banks. Our sample period covers the most turbulent period of September 8, 2008 through September 19, 2008, which spans Lehman Brothers bankruptcy filing. We get intra-day trading data, including bid and ask price, trade price, and volume, from TAQ (Trade and Automated Quotations).

Stocks are included and excluded in our samples according to the following criteria:

- ◆ If there are stock repurchases, stock splits, reverse splits, and dividend payoffs on the stocks, we exclude them from our samples.
- ◆ In order to observe the cross relation between international market, all of our sample stocks come from NYSE. For foreign investment banks, we choose the stocks listed on NYSE instead of the ones listed on their domestic stock exchanges, and thus do not exclude ADRs (American Depositary Receipts).
- ◆ We examine every quote during the transaction period, and the quotes with negative bid-ask spread are dropped.
- ◆ Any quote less than five seconds prior to the trade is ignored and the first one at least five seconds prior to the trade is retained.

We employ Lee and Ready (1991) trade assignment algorithm to assign buy- or seller-initiated, and calculate order imbalances by summing up the number of shares traded every 5, 10, and 15 minutes. The

average daily return is 0.0649%, with a median of -0.8841%.

We examine unconditional return-order imbalance through a regression for three time intervals (5, 10, and 15 minutes),

$$R_{i,t} = \alpha_0 + \alpha_1 OI_{j,t-1} + \alpha_2 OI_{j,t-2} + \alpha_3 OI_{j,t-3} + \alpha_4 OI_{j,t-4} + \alpha_5 OI_{j,t-5} + \varepsilon_t, \quad (1)$$

where $R_{i,t}$ is the current stock return of the three foreign investment banks, and is defined as $\ln(P_t/P_{t-1})$; $i = 1\sim 3$, which represents DB, UBS, NMR, respectively. $OI_{j,t}$ are lagged order imbalance at time t of the four US investment banks, and $j = 1\sim 4$, which represents BAC, C, GS, MS, respectively.

A positive return-imbalance relation is expected. Moreover, we observe the convergence path through 5-minute, 10-minute, to 15-minute intervals. The contemporaneous order imbalance is included in the above regression to examine conditional return-order imbalance relation. According to Chordia and Subrahmanyam (2004), we expect a positive contemporaneous and a negative lag return-order imbalance relation.

In order to explore the impact of volatility on return-imbalance, we employ a time varying GARCH for the three different time intervals (5-, 10-, and 15-minute):

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

where $R_{i,t}$ is the return in period t , and is defined as $\ln(P_t/P_{t-1})$; $I = 1\sim 3$, which represents DB, UBS, NMR, respectively. $OI_{j,t}$ is order imbalance in period t , $j=1\sim 4$, which represents BAC, C, GS, MS, respectively. β is the coefficient describing the impact of order imbalance on stock returns. Ω_{t-1} is the information set in period $t - 1$.

We expect a positive β with a decaying convergence process. Furthermore, another GARCH model is employed to investigate the direct link between volatility and order imbalance.

$$R_{i,t} = \alpha + \varepsilon_t, \\ \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t), \\ h_t = A + Bh_{t-1} + C\varepsilon_{t-1}^2 + \gamma * OI_{j,t}, \quad (3)$$

where $R_{i,t}$ is the return in period t , and is defined as $\ln(P_t/P_{t-1})$; $i = 1\sim 3$, which represents DB, UBS, NMR, respectively. $OI_{j,t}$ is order imbalance in period t , $j = 1\sim 4$, which represents BAC, C, GS, MS, respectively γ is the coefficient describing the im-

part of order imbalances on stock volatility. Ω_{t-1} is the information set in period $t-1$.

We expect a positive γ because intuitively a large volatility is followed by a large order imbalance.

Finally, we employ a nested causality to explore the dynamic causal relationship between return and order imbalance. According to Chen and Wu

$$Var(x_{1(T+1)} | \tilde{x}_1) = Var(x_{1(T+1)} | \tilde{x}_1, \tilde{x}_2) = Var(x_{1(T+1)} | \tilde{x}_1, \tilde{x}_2, \tilde{x}_{2(T+1)}). \tag{4}$$

and

$$Var(x_{2(T+1)} | \tilde{x}_2) = Var(x_{2(T+1)} | \tilde{x}_1, \tilde{x}_2) = Var(x_{2(T+1)} | \tilde{x}_1, \tilde{x}_2, \tilde{x}_{1(T+1)}). \tag{5}$$

Definition 2: Contemporaneous relationship, $x_1 \sim x_2$: x_1 and x_2 are contemporaneously related if:

$$Var(x_{1(T+1)} | \tilde{x}_1) = Var(x_{1(T+1)} | \tilde{x}_1, \tilde{x}_2), \tag{6}$$

$$Var(x_{1(T+1)} | \tilde{x}_1, \tilde{x}_2) > Var(x_{1(T+1)} | \tilde{x}_1, \tilde{x}_2, \tilde{x}_{2(T+1)}), \tag{7}$$

and

$$Var(x_{2(T+1)} | \tilde{x}_2) = Var(x_{2(T+1)} | \tilde{x}_1, \tilde{x}_2), \tag{8}$$

$$Var(x_{2(T+1)} | \tilde{x}_1, \tilde{x}_2) > Var(x_{2(T+1)} | \tilde{x}_1, \tilde{x}_2, \tilde{x}_{1(T+1)}). \tag{9}$$

Definition 3: Unidirectional relationship, $x_1 \Rightarrow x_2$.

There is a unidirectional relationship from x_1 to x_2 if

$$Var(x_{1(T+1)} | \tilde{x}_1) = Var(x_{1(T+1)} | \tilde{x}_1, \tilde{x}_2) \tag{10}$$

and

$$Var(x_{2(T+1)} | \tilde{x}_2) > Var(x_{2(T+1)} | \tilde{x}_1, \tilde{x}_2). \tag{11}$$

Definition 4: Feedback relationship, $x_1 \Leftrightarrow x_2$

There is a feedback relationship between x_1 and x_2 if

$$Var(x_{1(T+1)} | \tilde{x}_1) > Var(x_{1(T+1)} | \tilde{x}_1, \tilde{x}_2) \tag{12}$$

and

$$Var(x_{2(T+1)} | \tilde{x}_2) > Var(x_{2(T+1)} | \tilde{x}_1, \tilde{x}_2). \tag{13}$$

To explore the dynamic relationship within a bivariate system, we form the five statistical hypo-

(1999), we define four relationships between two random variables, x_1 and x_2 , in terms of constraint the conditional variances of $x_{1(T+1)}$ and $x_{2(T+1)}$ based on various available information sets, where $x_i = (x_{i1}, x_{i2}, \dots, x_{iT})$, $i = 1, 2$, 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

theses 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 whether there exists a specific causal relationship, we use a systematic multiple hypotheses testing method. Unlike the traditional pairwise hypothesis testing approach, this testing method avoids the potential bias induced by restricting the causal relationship to a single alternative hypothesis. To implement this method, we employ the results of several pair-wise hypothesis tests. For instance, in order to conclude that $x_1 \Rightarrow x_2$, we need to establish that $x_1 \not\Leftarrow x_2$ and to reject that $x_1 \not\Rightarrow x_2$. To conclude that $x_1 \Leftarrow x_2$, we need to establish that $x_1 \not\Leftarrow x_2$ as well as $x_1 \not\Rightarrow x_2$ and also to reject $x_1 \wedge x_2$.

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

$H_1: x_1 \wedge x_2$	$\varphi_{12}(L) = \varphi_{21}(L) = 0$, and $\sigma_{12} = \sigma_{21} = 0$
$H_2: x_1 \Leftarrow x_2$	$\varphi_{12}(L) = \varphi_{21}(L) = 0$
$H_3: x_1 \not\Rightarrow x_2$	$\varphi_{21}(L) = 0$
$H_3': x_2 \not\Rightarrow x_1$	$\varphi_{12}(L) = 0$
$H_4: x_1 \Leftarrow \Rightarrow x_2$	$\varphi_{12}(L)^* \varphi_{21}(L) \neq 0$
$H_5: x_1 \not\Rightarrow \Rightarrow x_2$	$\varphi_{21}(L) = 0$, and $\sigma_{12} = \sigma_{21} = 0$
$H_6: x_2 \not\Rightarrow \Rightarrow x_1$	$\varphi_{12}(L) = 0$, and $\sigma_{12} = \sigma_{21} = 0$
$H_7: x_1 \Leftarrow \Rightarrow \Rightarrow x_2$	$\varphi_{12}(L)^* \varphi_{21}(L) \neq 0$, and $\sigma_{12} = \sigma_{21} = 0$

Notes: The bivariate VAR model may be expressed as: $\begin{bmatrix} \varphi_{11}(L) & \varphi_{12}(L) \\ \varphi_{21}(L) & \varphi_{22}(L) \end{bmatrix} \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$, where x_{1t} and x_{2t} are mean adjusted variables. The first and second moments of the error structure, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ are that $E(\varepsilon_t) = 0$, and $E(\varepsilon_t \varepsilon_{t+k}) = 0$ for $k \neq 0$ and $E(\varepsilon_t \varepsilon_{t+k}) = \Sigma$ for $k = 0$, where

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}.$$

In other words, it is necessary to examine all five hypotheses in a systematic way before we draw the conclusion that a dynamic relationship exists. The following presents an inference procedure that starts from a pair of the most general alternative hypotheses.

Our inference procedure for exploring the 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 test

sintend 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.

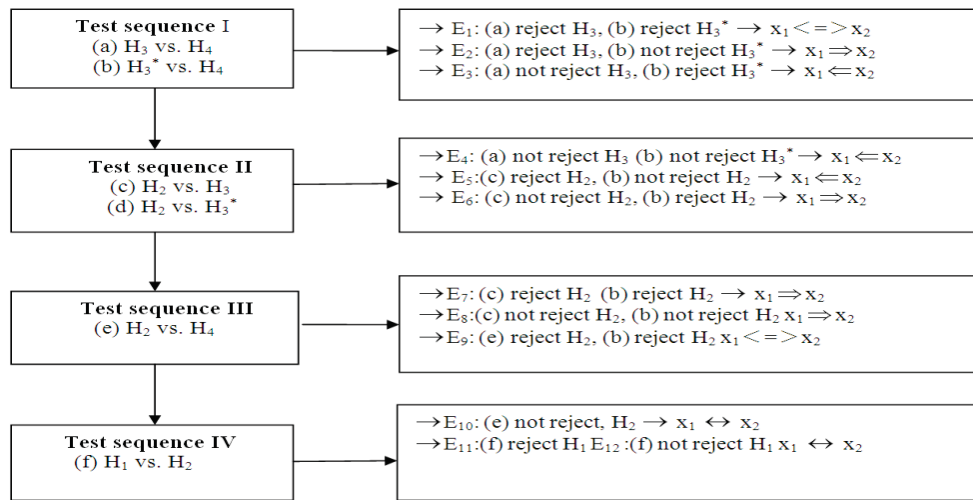


Fig. 1. Test flow chart of a multiple hypothesis testing procedure

2. Empirical results

2.1. Unconditional lagged return-order imbalance OLS relation. We run a regression with five lagged order imbalances to examine unconditional return-order imbalance relation. The results are exhibited in

Table 2. Our empirical results show that the coefficients of lagged-one order imbalances are nearly all positive. Specifically, at 5% significant level, the percentages reduced to 9.2%, 4.2%, and 5.0%, for 5-, 10-, and 15-minute interval, respectively.

Table 2. Unconditional lagged return-order imbalance relation

	Average coefficient	Percent positive and significant	Percent positive and significant	Percent negative and significant
5-min interval				
Olt-1	2.11809E-09	66.7%	9.2%	0.0%
Olt-2	6.83928E-10	57.5%	6.7%	0.0%
Olt-3	4.23575E-10	47.5%	5.0%	6.7%
Olt-4	8.16545E-10	45.8%	0.8%	6.7%
Olt-5	9.33534E-11	54.2%	1.7%	5.0%
10-min interval				
Olt-1	1.36798E-09	58.3%	4.2%	2.5%
Olt-2	-2.87594E-10	44.2%	5.0%	4.2%
Olt-3	-9.26014E-10	33.3%	4.2%	4.2%
Olt-4	-1.41958E-09	38.3%	1.7%	5.0%
Olt-5	-5.18489E-10	39.2%	0.8%	3.3%
15-min interval				
Olt-1	1.99004E-09	51.7%	5.0%	1.7%
Olt-2	-2.93517E-09	35.8%	0.8%	11.7%
Olt-3	-2.93279E-09	34.2%	0.8%	5.0%
Olt-4	-3.5752E-09	34.2%	0.0%	5.0%
Olt-5	-1.58706E-10	46.7%	7.5%	3.3%

Notes: "Significant" denotes significant at the 5% level.

We find that the percentages of significantly positives are not declining steadily from 5- to 15-minute interval, but with an apparent slump under 10-minute interval and then back to higher numbers, which is inconsistent with Chordia et al. (2005). The relatively low prediction power in our results implies the particular market condition. We observe low percentage of significantly positive lagged-one, which indicates that market is efficient.

For the particular slump observed in 10-minute interval, the authors argue that 10-minute interval is

the most appropriate time for market makers to adjust their inventories and mitigate volatility, especially in a turbulent market.

2.2. Conditional contemporaneous return-order imbalance OLS relation. The authors conduct a regression with contemporaneous and four lagged order imbalances to examine conditional contemporaneous return-order imbalance relation. The results are presented in Table 3.

Table 3. Conditional contemporaneous return-order imbalance relation

	Average coefficient	Percent positive and significant	Percent positive and significant	Percent negative and significant
5-min interval				
Olt-1	1.09532E-08	98.3%	89.2%	0.8%
Olt-2	1.65261E-09	58.3%	7.5%	0.0%
Olt-3	7.48376E-10	54.2%	6.7%	2.5%
Olt-4	1.25681E-10	48.3%	7.5%	10.0%
Olt-5	-7.74292E-10	34.2%	1.7%	3.3%
10-min interval				
Olt-1	1.25865E-08	97.5%	75.0%	0.0%
Olt-2	2.99232E-10	51.7%	3.3%	8.3%
Olt-3	-4.12773E-10	39.2%	6.7%	7.5%
Olt-4	-1.11621E-09	31.7%	1.7%	3.3%
Olt-5	-1.00667E-09	36.7%	2.5%	4.2%
15-min interval				
Olt-1	1.36211E-08	97.5%	66.7%	0.0%
Olt-2	-1.13767E-10	37.5%	5.0%	5.8%
Olt-3	-2.6757E-09	34.2%	1.7%	8.3%
Olt-4	-2.09129E-09	38.3%	0.0%	6.7%
Olt-5	-2.2375E-09	41.7%	1.7%	2.5%

Notes: "Significant" denotes significant at the 5% level.

The empirical findings show that, for all time intervals, contemporaneous order imbalances are significantly positives. Specifically, from 5- to 15-minute interval, the percentages of significantly positives fall from 89.2% to 66.7%, at 5% significant level, respectively. We find a clear convergence pattern to market efficiency.

However, the authors can not find the reversal effects on lagged order imbalance in 5-minute interval, which is inconsistent with Chordia and Subrahmanyam (2004), and Andrade et al. (2008)¹. Our empirical results can be explained either by low autocorrelation between order imbalances caused by liquidity trader's behavior or by market maker's slow reaction to order imbalances. We explain the empirical results through market maker behaviors.

¹ We run the unit root test on seven sample companies and find that there are no unit root on every company. Thus, the findings are not spurious. For robustness, we allow for a nonlinear relation between returns and order imbalances. The results are similar after we add the square terms of order imbalances. Therefore, there is no model misspecification.

Normally, market makers expect that order flow in the same direction come consecutively and thus inventory pressures rise from the same direction. The inventory pressures will also rise for other stocks, especially for spillover effect in the same industry, as proposed by Andrade et al. (2008). But during our testing period, market makers do not anticipate such order flow for international investment bank stocks and react slowly in 5-minute interval; namely, the prices in the previous trading period do not fully reflect potential order imbalance in the current period, and market makers continue to adjust prices in the current period, which results a significantly positive lag return-order imbalance relation.

2.3. Dynamic return-order imbalance GARCH relation. In order to explore impact of volatility on return-imbalance, we employ a time varying GARCH. The results are presented in Panel A of Table 4. Compared to regression results, order imbalances are still positively related to return, but the percentage of significantly positives dropped dramatically. At 5% significant level, the significantly positives of β , denoted coefficient of impact of order imbalance on return, are 41.7%, 40.7%, and 20.0%,

for 5-, 10-, and 15-minute interval, respectively. The authors confirm convergence pattern in GARCH model, but the predicting power of order

imbalances is much weaker than that in regression, which implies volatility plays a role in return-order imbalance relation.

Table 4. Dynamic return (volatility)-order imbalance GARCH (1.1) relation

Panel A: Dynamic volatility-order imbalance GARCH (1.1) relation		
	Percent positive and significant	Percent negative and significant
5-min interval	41.7%	4.2%
10-min interval	40.7%	0.0%
15-min interval	20.0%	0.0%
Panel B: Dynamic return (volatility)-order imbalance GARCH (1.1) relation		
	Percent positive and significant	Percent negative and significant
5-min interval	4.2%	10.0%
10-min interval	3.3%	1.7%
15-min interval	0.0%	0.0%

Notes: “Significant” denotes significant at the 5% level.

2.4. Dynamic volatility-order imbalance GARCH (1,1) relation. In order to investigate the direct link between volatility and order imbalance, we make a further step to examine dynamic volatility-order imbalance relation. The results are shown in Panel B of Table 4.

Intuitively, a large volatility is followed by a large order imbalance. Therefore, we expect a positive relation between order imbalances and volatility. However, our empirical results show a totally different picture. We find a negatively related volatility-imbalance relation, especially under 5-minute interval. Two possible explanations are associated with negative volatility-order imbalance relation. First, Kahneman and Tversky (1979) proposed the “prospect theory” arguing that investors tend to hold their stocks on hand when stock prices rise, but tend to overreact and to sell their holdings in panic when prices drop. The other story comes from Christie (1982)’s leverage effect. He found that debt-to-equity ratio could be a possible explanation for the negative relationship between stock market returns and changes in volatility. When stock prices drop, market caps shrink to increase debt to equity ratio. The increases in leverage result in a higher volatility. During our sample period, market value dropped on average 4.54%. Both theories explain the negative volatility-order imbalance relation.

We also find that the negative relation between order imbalances and volatility disappears quite fast. From 5- to 10-minute interval, the percentage of negative coefficients drops from 10.0% to 1.7%, at 5% significant level, and within 15 minutes, the impact of order imbalances on volatility almost fades away. This implies that market makers have the ability to mitigate volatility through inventory adjustments.

2.5. Order imbalance based trading strategy. We try to develop an imbalance based trading strategy to test market efficiency. We sort out the largest 10% discretionary trades in each day for 5-, 10-, and 15-minute time intervals to rule out noisy trades. We long at buyer-initiated and short at seller-initiated. The trading performances with associated tests are reported in Tables 5 and 6.

2.5.1. Trading performances based on same period trade. By applying our trading strategy based on same period trade, we get an average daily return of 1.13%, 0.69%, and 1.18%, for 5-, 10-, and 15-minute time interval, respectively. Three hypothesis tests are then performed at 5% significant level to further evaluate our strategy. First, a z-test is used to examine whether our trading strategy can earn a positive return. The p-values are 0.00014, 0.59568, and 0.78166, for 5-, 10-, and 15-minute interval, respectively. We find that we have a positive performance in 5-minute interval and our strategy beat the market under all time intervals at 5% significant level.

Table 5. Trading profit by trading on current period

Panel A: Returns compared with zero		
1. $\left\{ \begin{array}{l} H_0 : \mu_i \leq 0 \\ H_0 : \mu_i > 0 \end{array} \right\}$		
		P-value
5-min return of strategy		
Panel B: Returns compared with returns of buy-and-hold strategy		
10-min return of strategy		
15-min return of strategy		

Table 5 (cont.). Trading profit by trading on current period

Panel B: Returns compared with returns of buy-and-hold strategy		
10-min return of strategy		
15-min return of strategy		
2. $\begin{cases} H_0 : \mu_i \geq \mu_0 \\ H_1 : \mu_i < \mu_0 \end{cases}$		
	Mean	P-value
Original open-to-close return	1.13%	
5-min return of strategy	1.15%	0.472893231
10-min return of strategy	-0.10%	0.122366369
15-min return of strategy	-0.45%	0.062778774
Panel C: Differences in returns among the three intervals		
3. $\begin{cases} H_0 : \mu_i = \mu_j \\ H_1 : \mu_i \neq \mu_j \end{cases}$		
P-value	5-min return	10-min return
10-min return	0.059336193	0.608106021
15-min return	0.015493565	

Table 6. Trading profit by trading on current period

Panel A: Returns compared with zero		
1. $\begin{cases} H_0 : \mu_i \leq 0 \\ H_1 : \mu_i > 0 \end{cases}$		
		P-value
5-min return of strategy		
10-min return of strategy		
15-min return of strategy		
Panel B: Returns compared with returns of buy-and-hold strategy		
2. $\begin{cases} H_0 : \mu_i \geq \mu_0 \\ H_1 : \mu_i < \mu_0 \end{cases}$		
	Mean	P-value
Original open-to-close return	1.13%	
5-min return of strategy	1.15%	0.472893231
10-min return of strategy	-0.10%	0.122366369
15-min return of strategy	-0.45%	0.062778774
Panel C: Differences in returns among the three intervals		
3. $\begin{cases} H_0 : \mu_i = \mu_j \\ H_1 : \mu_i \neq \mu_j \end{cases}$		
P-value	5-min return	10-min return
10-min return	0.059336193	0.608106021
15-min return	0.015493565	

2.5.2. *Trading strategy based on lagged period trade.* Based on lagged period trade, we get an average daily return of 0.01%, -1.47%, and -0.82%, for 5-, 10-, and 15-minute time interval, respectively. Apparently, these daily returns base on the trading strategy are not significantly larger than zero. Similarly, a paired *t*-test is applied then to test whether the returns can beat the original daily return, although the returns are not larger than zero. The testing results show that, at 5% significant level, our strategy cannot beat the market. It implies the market efficiency in financial crisis.

2.6. **The causal relationship in explaining the return-order imbalance relationship.** To explore the dynamic return-order imbalance relationship during the price formation process, we employ a nested causality approach. In order to investigate the dynamic relationship between two variables, we impose the constraints in the upper panel of Table 1 for the VAR model. In Table 7, the authors present the empirical results of the tests of the hypotheses for the dynamic relationship in Table 1.

Table 7. Dynamic nested causality relationship between returns and order imbalances

	$x_1 \wedge x_2$	$x_1 \leftarrow x_2$	$x_1 \Rightarrow x_2$	$x_1 \Leftarrow x_2$	$x_1 \leq x_2$
All trade size	0.00%	85.71%	14.29%	0.00%	0.00%

For the entire sample, we show that the unidirectional relationship from returns to order imbalances is 14.29% of the sample firms for the entire sample, while the unidirectional relationship from order imbalances to returns is 0.00%. The percentage of firms that fall into the independent category is 0.00%. Moreover, 85.71% of firms exhibit a contemporaneous relationship between returns and order imbalances. Finally, 0.00% of firms exhibit a feedback relationship between returns and order imbalances. The percentage of firms exhibiting a unidirectional relationship from order imbalances to returns is smaller than that exhibiting such a unidirectional relationship from returns to order imbalances, suggesting that order imbalances do not constitute a better indicator for predicting future returns. This finding 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). In addition, the percentage of firms exhibiting a contemporaneous relationship is much larger than that of the corresponding percentage reflecting a feedback relationship, indicating the interaction between returns and order imbalances in the current period is larger than that over the whole period.

Conclusion

With a view toward better understanding of how stock prices move and the process of market efficiency, many previous literatures have documented extensively the relation between trading activities and stock returns. In this paper, we use order imbalances as the proxy for trading activities. The main purpose of our study is to investigate the convergence process toward efficiency of international

investment banks in the stock market, particularly during the financial crisis in September 2008.

We examine conditional and conditional return-order imbalance relations. We find that the impacts of lagged imbalances on returns are positive across different stocks, but the magnitude is relatively small when compared to the results in Chordia and Subrahmanyam (2004). This weaker prediction power attributed to investor's behavior during financial crisis. Our empirical findings on conditional return-imbalance show current imbalances are positively related to returns.

We confirm our findings through a time varying GARCH. Similar to the regression results, we find that imbalances are still positively related to return, but the percentage of positive coefficients dropped dramatically. It implies that a large part of the explaining power is from risk premium rather than order imbalance during financial crisis. We take a further step to examine volatility-order imbalance relation. We find a small but negative relation between imbalances and volatility. Two explanations are provided. The first one is from Kahneman and Tversky (1979)'s prospect theory, and the other is from Christie (1982)'s leverage effect. Both theories explain the negative relation between volatility and imbalances when the market declines. We develop an imbalance based trading strategy to test market efficiency. The performances are generally poor and cannot beat the market during our testing period, unless we use same period trade which is almost impossible in the real world. Finally, we also employ a nested causality approach to examine the dynamic return-order imbalance relationship during the price-formation process. The results explain our findings.

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