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Market Efficiency of Commercial Bank in Financial Crisis

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ABSTRACT

This study investigates commercial bank market efficiency in financial crisis. We employ a time-varying generalized autoregressive conditional heteroskedasticity (GARCH) model because volatility matters in financial crisis. The empirical results show a significant positive relation between contemporaneous order imbalances and returns in convergence process toward efficiency. A direct linkage between volatility and order imbalances is examined by GARCH model. Surprisingly, a low connection exists between order imbalance and price volatility, implying that market makers are capable of mitigating commercial bank prices volatility in financial crisis. We develop an imbalance based trading strategy but fail to beat the market. A nested causality approach, which examines the dynamic return-order imbalance relationship during the price formation process, confirms the results.

Keywords: Order Imbalance, Market Efficiency, Commercial Bank, Financial Crisis
JEL Classifications: G01, G14, G21

1. INTRODUCTION

The global financial crisis has led to renewed criticism of the efficient-market hypothesis (EMH). As one prominent example, market strategist Jeremy Grantham has stated that EMH is responsible for the current financial crisis and claim that belief in the EMH caused financial leaders to have a "chronic underestimation of the dangers of asset bubbles breaking"[1]. Renowned financial journalist and best-selling author Roger Lowenstein blasted the theory, stating "The upside of the current Great Recession is that it could drive a stake through the heart of the academic nostrum known as the EMH"[2].

The main purpose of our study is to investigate market efficiency in 2008 financial crisis in the U.S., which is the leading and most efficient stock market in the world. Therefore, the magnitude of effect is far greater than 1997 financial crisis. We especially focus on market efficiency of commercial banks. Beginning in the 1980s, players in the U.S. mortgage market started to transfer the risk to other players, and some of these players are commercial banks, where customers deposit their money into checking or savings accounts. Commercial banks are also lending institutions. They provide mortgages and other types of loans to their customers, and in some cases pass these mortgages to other institutions. These mortgages are bundled into securities and sold to large investment banks and the government-sponsored entities Fannie Mae and Freddie Mac to get mortgage debt off their books. In this way, commercial banks have the capacity to make more loans.

Besides, commercial banks have an incentive to seek low-risk assets to meet the capital adequacy requirements which were set forth by the Basel Committee on Banking Regulation. Commercial banks not only look for low-risk assets, but also seek assets that produce high yields on their investment to increase profit. Commercial banks in the U.S. and worldwide thus have an incentive to purchase assets that entail little risk and do not require them to keep large amounts of capital on hand. Through securitization, the U.S. investment banks and other financial institutions pool many different types of assets, including risky subprime mortgages, to make assets "safer" and thus attract commercial banks. As a result, commercial banks invested heavily

1 Cited in a widely read New York Times business column, Joe Nocera, "Poking Holes in a Theory on Markets," New York Times, June 5, 2009. http://www.nytimes.com/2009/06/06/business/06nocera.html?scp=1&sq=efficient%20 market&st=cse. See also Grantham's foreword in Andrew Smithers, Wall Street Revalued: Imperfect Markets and Inept Central Bankers (Chichester, UK: Wiley, 2009).
2 On Wall Street, the Price isn't Right." Washington Post. 7 June, 2008.

in subprime mortgage-backed securities to get a greater yield for the same amount of risk.

However, during financial crisis period, these “safer” assets became toxic assets that banks were no longer able to value and that were worth so little on the market. Thus, they have become virtually un-sellable when credit rating agencies realized that the assets they had rated as AAA, or very low-risk, were actually much riskier. Furthermore, according to mark-to-market accounting rules, commercial banks are required to value mortgage backed securities and collateralized debt obligation based on their market price, but banks were no longer able to value them accurately because there was no way of determining their risk. Those that are able to sell their assets on the market made a great loss because the market prices of those assets were much lower than the assets’ original values. Since these assets were sold for such a low price, commercial banks that did not sell their assets had to lower the value of, or “write down,” the assets on their balance sheets in order to “mark to market.” These write-downs hurt banks even when they were not planning to sell the assets.

We can infer that there would be a large impact on commercial banks in financial crisis since these banks have toxic assets. Thus, we observe the relation between order imbalances and returns to investigate whether informed traders have more inside information such as how many toxic assets commercial banks have and how many debts are removed from balance sheet through securitization process, and then they are able to get abnormal return.

There are some researches on stock market efficiency in 1997 financial crisis. Hoque et al., (2007) investigate the weak-form efficiency of eight Asian stock markets by adopting variance ration tests for the pre-crisis (1990-1997) and post-crisis (1998-2004) periods. They indicate that the crisis does not have significant effect on the efficiency degree, and six of the Asian markets continue inefficient after the crisis, while Korea has the opposite result. Taiwan market is the only one that gets improvement in efficiency from the pre-crisis to post-crisis period. Jae and Shamsuddin (2008) find that there is no significant change in the degree of market efficiency by using multiple variance ratio tests. Lim et al. (2006) conjecture that the nonlinear serial dependency structure is attributed to unexpected shocks. They argue that investors were swamped by panic, and this adversely affected the market’s ability to price stock efficiently. Cheong et al. (2007) separate the sample data into four periods, that is, pre-crisis, crisis, USD pegged, and post-crisis period. Their study shows that the highest inefficiency is during the crisis period, followed by pre-crisis, post crisis, and USD pegged period. Lim et al. (2008) investigate eight Asian stock markets’ efficiency in the 1997 financial crisis for pre-crisis, crisis, and post-crisis periods by using the rolling bi-correlation test statistic. Their result presents that the crisis badly affected the efficiency of most Asian stock markets, with Hong Kong being strike severely, yet most of these markets’ efficiency get improved in the post-crisis period. They also indicate that investors would overreact not only to local news, but also news from other markets, particularly adverse news. Moreover, Choudhry and Jayasekera (2015) examine twenty five UK firms of different sizes and from different industries from 2004 to 2010, which includes the current global financial crisis. They find that most firms and industries seem to support the market efficiency hypothesis during good periods (booms) and bad periods (recessions). However, the level of market efficiency seems to decline significantly from the pre-crisis to crisis period. Both the results of market efficiency and declining market efficiency from the pre-crisis to crisis periods support the asymmetric effect of the financial crisis on the beta of UK firms.

In brief, most of previous studies about efficiency in financial crisis show that market cannot achieve efficiency during market crash period. Moreover, some researchers observe the trading volume or order imbalances to investigate the behavior of informed traders and examine whether there exists information asymmetry.

In our study, we use order imbalance to investigate relations among intraday stock return, volatility and order imbalances of commercial banks during financial crisis. We choose short event window in order to minimize the noise arising from random price movements and errors owing to misestimates of benchmark returns. Chordia et al. (2002) find that the order imbalances are strongly related to past market returns and are strongly related to contemporaneous absolute returns after controlling for market volume and market liquidity. Order imbalance increases (decrease) after market declining (rising), which shows that investors are contrarians on aggregate. However, either excess buyer- or seller-initiated order imbalances reduces liquidity. Moreover, order imbalances affect market returns even after controlling for aggregate volume and liquidity. Guillermo et al. (2002) adopt a simple model, in which the investors trade for two reasons which is to share risk or to speculate upon private information. They argue that the relation between current returns, volume, and future returns depends on the relative significance of speculative trade versus hedging trade. They find that returns generated by speculative trades tend to continue themselves, while returns generated by hedging trades tend to reverse themselves. Moreover, they also find that smaller firms with higher bid-ask spread tend to maintain their returns following high volume.

Chordia and Subrahmanyam (2004) test the relation between order imbalances and daily returns of individual stocks. They find that contemporaneous imbalances are strongly related to contemporaneous returns, but the positive relation between lagged imbalance and returns disappears after controlling for the contemporaneous imbalances. In addition, individual stock order imbalances are strongly and auto-correlated. Chordia et al. (2005) provide the relation between order imbalances and stock returns for different intervals. They find that order imbalances are highly positively dependent over both short and long time intervals. They argue that market can achieve weak-form efficiency between 5 and 6 min.

In our study, we don’t find a significant positive relation between current stock returns and lagged-one order imbalances. The empirical results show that within 10 or 15 min interval, market makers adjust inventories to mitigate volatility. We separate overall effect, auto-correlated effect, and cross-correlated effect. In overall effect, a significant negative relation between current returns and order imbalances is observed, and this result is contrary to cross-correlated effect situation. The contemporaneous order imbalances are significantly positive for all time intervals at 1% level, while most of the coefficients of lagged-one imbalances turn to be significantly negative, which is consistent with Chordia and Subrahmanyam (2004). We also document a convergence process from 5 min interval to 15 min interval. Our trading strategies are not capable of beating the market.

Our study proceeds as follows. Section 2 describes data. Section 3 presents the return-order imbalances relation. We discuss the dynamic return (volatility)-order imbalance generalized autoregressive conditional heteroskedasticity (GARCH) relation in Section 4. Section 5 shows the market efficiency testing through an imbalance-based trading strategy. We exhibit Dynamic causal relationship in explaining the return-order imbalance relationship in Section 6, and Section 7 concludes.

2. DATA

Major U.S. commercial banks are included in our samples. We observe commercial bank efficiency from September 9 to September 18, 2008, namely 4 days before and after Lehman Brothers bankruptcy. We collect intraday transactions data from Trade and Quote (TAQ).

Stock are included or excluded depending on the following criteria. First, the firm must be included in both the Compustat and TAQ database. Second, the top four commercial banks (Bank of America, Wells Fargo, City Bank, and American Express) are listed in NYSE based on liquidity and size concern. Third, we delete transactions within the first 90 s after the opening of the market to avoid noise trading. Fourth, quotes established and transactions traded before the opening or after the close are excluded.

3. RETURN-ORDER IMBALANCES RELATION

We apply Lee and Ready (1991) trade assignment algorithm on intraday returns and order imbalances for 5-, 10-, and 15-min time intervals. We use a multi-regression to examine the impact of five lagged order imbalances on current stock returns for three different time intervals.

$$R_t = \alpha_0+\alpha_1\, OI_{t-1}+\alpha_2\, OI_{t-2}+\alpha_3\, OI_{t-3}+\alpha_4\, OI_{t-4}+\alpha_5\, OI_{t-5}+\varepsilon_t \tag{1}$$

Where R_t is the current stock return of the individual stock. OI_{t-i} are the lagged order imbalances at time $t-1$, $t-2$, $t-3$, $t-4$, and $t-5$ of the sample stocks.

An imbalance-based trading strategy is developed on the condition that order imbalances have a significant impact on return. We also include contemporaneous and four lagged order imbalances to examine conditional lagged return- order imbalance regression relation for three time intervals. According to Chordia and Subrahmanyam (2004), we expect a positive relation between contemporaneous imbalances and current returns, and a negative relation between current returns and lagged order imbalances after controlling for the contemporaneous order imbalances because of information over-weighting of market makers. Moreover, we observe how market makers dynamically accommodate the imbalances pressure by examining whether there is a trend among three different time intervals (5-, 10-, 15-min).

Table 1 presents the percentages of positive and significant coefficients of lagged-one order imbalance are 3.9%, 3.9%, and 3.9% in 5-, 10-, and 15-min intervals respectively. From Panel A, we observe that the percentage of positive and significant of lagged-one order imbalance is higher than negative and significant

Table 1: Empirical results of unconditional lagged return-order imbalance relation

Effect	5 min interval (%)		10 min interval (%)		15 min interval (%)	
	Positive and significant	Negative and significant	Positive and significant	Negative and significant	Positive and significant	Negative and significant
Panel A overall effect situation						
OI_{t-1}	3.9	2.3	3.9	8.6	3.9	5.5
OI_{t-2}	2.3	0.0	0.0	7.0	1.6	10.2
OI_{t-3}	3.9	9.4	2.3	6.3	1.6	0.8
OI_{t-4}	2.3	7.0	0.8	7.8	0.0	7.0
OI_{t-5}	6.3	1.6	0.0	1.6	7.0	2.3
Panel B autocorrelated effect situation						
OI_{t-1}	0.00	6.25	3.13	9.38	3.13	3.13
OI_{t-2}	0.00	0.00	0.00	9.38	3.13	9.38
OI_{t-3}	3.13	12.50	3.13	3.13	0.00	3.13
OI_{t-4}	0.00	0.00	0.00	6.25	0.00	6.25
OI_{t-5}	6.25	3.13	0.00	0.00	3.13	3.13
Panel C cross-correlated effect situation						
OI_{t-1}	5.12	1.04	4.17	8.33	4.17	6.25
OI_{t-2}	3.13	0.00	0.00	6.25	1.04	10.42
OI_{t-3}	4.17	8.33	2.08	7.29	2.08	0.00
OI_{t-4}	3.13	9.38	1.04	8.33	0.00	7.29
OI_{t-5}	6.25	1.04	0.00	2.08	8.33	2.08

$R_t=\alpha_0+\alpha_1\, OI_{t-1}+\alpha_2\, OI_{t-2}+\alpha_3\, OI_{t-3}+\alpha_4\, OI_{t-4}+\alpha_5\, OI_{t-5}+\varepsilon_t$. Where R_t is the stock return at time t of the sample stock, OI_t is the lagged order imbalances at time t of the sample stocks, ε_t is the residual of the stock return at time. "significant" denotes significant at the 5% level one in 5 min interval, but both are insignificant. Surprisingly, significantly negative lagged-one imbalance is much larger then positive in 10 min interval at 10% and 5% significant level and in 15 min interval at 10% significant level. This finding can be explained as follows. When negative information shock occurs during financial crisis, informed traders eager to short stocks. They herd or spread their orders out over time, which causes a huge negative order imbalance. Confronted with the imbalance pressure, market makers react against that by reducing the quote price within 5 min interval, and the lower price does mitigate the pressure of selling for a while. We infer that within 10 min interval or 15 min interval would be a better interval for market makers to adjust inventories. Therefore, they raise quote prices and cause positive 10 min and 15 min returns, which leads to a negative relation between lagged-one imbalance and returns.

In addition, we find that the percentage of negative and significant lagged-three imbalances is relatively high in comparison with that of other lagged imbalances under 5 min interval. It implies that market makers are not able to determine whether the large order imbalance is caused by informed traders or not. Thus, they wait for two periods to confirm and start to adjust quote price back to normal level. Moreover, except for lagged-one and lagged-two imbalances under 5 min interval, the percentage of all significantly negative lagged imbalances are much larger than positive one in other lagged order imbalances, indicating that they tend to adjust quote price back to normal level gradually to offload their inventory rather than to correct at a stroke after they react by lowering or raising quote price in the beginning.

Panel B summarizes the empirical results of return on its own order imbalance at 5% significant level. The ratios of positive and significant coefficients of lagged-one order imbalance are 0%, 3.13%, and 3.13% under 5-, 10-, and 15-min intervals respectively. In contrast to the result of previous overall effect, the ratio of significantly negative lagged-one imbalance is larger than positive one under 5 min interval at 10% and 5% significant level, which is inconsistent with Chordia and Subrahmanyam (2004). It indicates that market makers react immediately and efficiently at the moment confronted with auto order imbalances. We presume that market makers know private information before shock arrives in financial crisis period, and market makers had already prepared enough inventories to accommodate order imbalance shocks.

Panel C illustrates findings of returns on order imbalances from other stocks, namely cross effect at 5% significant level. The percentages of positively significant coefficients of lagged-one order imbalance are 5.21%, 4.17%, and 4.17% under 5-, 10-, and 15-min intervals respectively. The result of cross-correlated effect is similar to overall effect. Andrade et al. (2008) explain that a demand shock for only one stock affects prices of other stocks due to the hedging desires of liquidity providers. In Panel C, the ratio of significantly positive coefficient of lagged-one imbalance is larger than negative one, which is contradict to auto-correlated effect. The possible explanation is as follows. Market makers, as liquidity providers, execute buy orders if they meet other stocks' buy orders from other traders for liquidity and hedging concerns just as what is mentioned above. They tend to raise quote price to induce other traders to sell in order to maintain their inventory level. Therefore, demand shock from other stock induce market makers to raise quote price of the individual stock, thus bring about positive relation between returns and lagged -one imbalances.

Table 2 presents that contemporaneous order imbalances are significantly positive at all significant levels and under all time intervals in overall effect, auto-correlated effect, and cross-correlated effect situation, while most of the coefficients of

Table 2: Empirical results of conditional contemporaneous return-order imbalance relation

Effect	5 min interval (%)		10 min interval (%)		15 min interval (%)	
	Positive and significant	Negative and significant	Positive and significant	Negative and significant	Positive and significant	Negative and significant
Panel A overall effect situation						
OI_t	96.1	0.0	86.7	0.0	75.8	0.0
OI_{t-1}	2.3	8.6	2.3	11.7	2.3	10.2
OI_{t-2}	2.3	2.3	0.8	5.5	2.3	7.0
OI_{t-3}	5.5	7.0	5.5	3.1	0.0	0.8
OI_{t-4}	96.1	0.0	86.7	0.0	75.8	0.0
Panel B autocorrelated effect situation						
OI_t	100.00	0.00	100.00	0.00	96.88	0.00
OI_{t-1}	0.00	15.63	3.13	9.38	3.13	12.50
OI_{t-2}	0.00	3.13	0.00	12.5	3.13	3.13
OI_{t-3}	3.13	12.50	3.13	0.00	0.00	0.00
OI_{t-4}	0.00	3.13	3.13	3.13	0.00	3.13
Panel C cross-correlated effect situation						
OI_t	94.79	0.00	82.29	0.00	68.75	0.00
OI_{t-1}	3.13	6.25	2.08	12.50	2.08	9.38
OI_{t-2}	3.13	2.08	1.04	3.13	2.08	8.33
OI_{t-3}	6.25	5.21	6.25	4.17	0.00	1.04
OI_{t-4}	1.04	9.38	1.04	11.46	1.04	2.08

$R_t=\alpha_0+\alpha_1 OI_{t-1}+\alpha_2 OI_{t-2}+\alpha_3 OI_{t-3}+\alpha_4 OI_{t-4}+\alpha_5 OI_{t-5}+\varepsilon_t$. Where R_t is the stock return at time t of the sample stock, OI_t is the lagged order imbalances at time t of the sample stocks, ε_t is the residual of the stock return at time. "significant" denotes significant at the 5% level lagged-one imbalances turn to be significantly negative, which is consistent with Chordia and Subrahmanyam (2004). They argue that the positive relation between lagged imbalances and returns disappears after controlling for the current imbalance. Market makers overweight the impact of current trades which are auto-correlated with past trades, as a consequence they reverse the quote price to offset the overreaction in next period.

From Panels B and Panel C of Table 2, we find that the result of auto-correlated and cross-correlated effect are similar. It implies that in these two conditions, market makers have concern for information contained in order imbalances and inventory risk. Nonetheless, the magnitude is larger in auto-correlated effect because market makers tend to adjust inventory level by degree of correlation of stocks, and correlation in cross-correlated effect is lower than that of individual stock.

4. DYNAMIC RETURN (VOLATILITY) - ORDER IMBALANCE GARCH RELATION

In order to explore the impact of volatility on return-order imbalance relation, we adopt a time-varying GARCH model. We use the model to examine the dynamic relation between returns and order imbalances under three different time intervals (5 min, 10 min, and 15 min):

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

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

$$h_t = A + Bh_{t-1} + C\varepsilon_{t-1}^2 \quad (2)$$

Where R_t is the return at time t, and is defined as $\ln P_t - \ln P_{t-1}$. OI_t denotes the explanatory variable of order imbalance. β is the coefficient describing the impact of order imbalance on stock returns. ε_t is the residual value of the stock return at time *t*. h_t is conditional variance at time *t*. Ω_{t-1} is the information set in at time $t-1$.

Intuitively, a large order imbalance is positively associated with a large volatility. We expect a significant positive β. Furthermore, we examine how long it takes for commercial bank market to achieve efficiency. Therefore, we adopt a GARCH model to investigate whether a larger order imbalances lead to a larger price volatility under three different time intervals.

The empirical results of dynamic return-order imbalance GARCH relation have been presented in Table 3. In contrast with the results in the above regression models, there exists a clear convergence process. At 5% significant level, the proportion of significantly positive β are 71.88%, 43.75%, and 28.13% under 5-, 10-, and 15-min interval respectively in auto-correlated effect, and 51.04%, 35.42%, and 18.75% under 5-, 10-, and 15-min interval respectively in cross-correlated effect. From the empirical findings, we confirm the important role of volatility on return-order imbalance relation.

The relation between price volatility and order imbalance is also an important issue in our study. We expect that there is a positive correlation between price volatility and order imbalances, that is, large price volatility is accompanied by large order imbalances. The results are presented in Table 4.

We observe that the proportion of significantly positive or negative coefficients of order imbalances is not as large as we expect, indicating that the impact of order imbalance on volatility is not as strong as we expect. At 5% significant level, the proportion of significantly positive β are 9.38%, 0%, and 0% under 5-, 10-, and 15-min interval respectively in auto-correlated effect, and 6.25%, 1.04%, and 1.04% under 5-, 10-, and 15-min interval respectively in cross-correlated effect. The low connection between order imbalances and price volatility could be explained that market makers show the capability of mitigating commercial banks' price volatility in financial crisis.

Table 3: Empirical results of the dynamic return-order imbalance GARCH (1, 1) relation

Effect	Percent positive and significant (%)	Percent negative and significant (%)
Panel A overall effect		
5 min interval	56.25	0.78
10 min interval	37.50	2.34
15 min interval	21.09	0.78
Panel B auto correlated effect		
5 min interval	71.88	0.00
10 min interval	43.75	3.13
15 min interval	28.13	0.00
Panel C cross-correlated effect		
5 min interval	51.04	1.04
10 min interval	35.42	2.08
15 min interval	18.75	1.04

$R_t = \alpha + \beta OI_t + \varepsilon_t$, $\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$, $h_t = A + Bh_{t-1} + C\varepsilon_{t-1}^2$ Where R_t is the return at time *t*, and defined as $\ln(P_t)-\ln(P_{t-1})$, OIt denotes the explanatory variable of order imbalance, β is the coefficient describing the impact of order imbalance on stock returns, h_t is the conditional variance at time *t*, Ω_{t-1} is the information set in at time $t-1$. "Significant" denotes significant at the 5% level

Table 4: Empirical results of the dynamic volatility-order imbalance GARCH (1, 1) relation

Effect	Percent positive and significant (%)	Percent negative and significant (%)
Panel A overall effect		
5 min interval	7.03	7.81
10 min interval	0.78	3.13
15 min interval	0.78	0.78
Panel B auto correlated effect		
5 min interval	9.38	6.25
10 min interval	0.00	3.13
15 min interval	0.00	0.00
Panel C cross-correlated effect		
5 min interval	6.25	8.33
10 min interval	1.04	3.13
15 min interval	1.04	1.04

Where R_t is the return at time *t*, and is defined as $\ln(P_t)-\ln(P_{t-1})$, OI_t denotes the explanatory variable of order imbalance. ε_t is the residual value of the stock return at time *t*. h_t is the conditional variance at time *t*, Ω_{t-1} is the information set in at time *t*, γ is the coefficient describing the impact of the order imbalance on volatility of the return. "significant" denotes significant at the 5% level

5. MARKET EFFICIENCY TESTING THROUGH AN IMBALANCE BASED TRADING STRATEGY

We take a further step to test market efficiency through an intraday imbalance based trading strategy. We truncate 10% of the largest order imbalance to trade under 5-, 10-, and 15-min interval. We buy when positive order imbalance appears, and short when it turns negative. The results are presented in Table 5.

Panel B shows that we earn a daily return of 0.38%, −0.85%, and −0.05% under 5-, 10-, and 15-min interval respectively in auto-correlated effect; 0.49%, −0.29%, −0.06% under 5-, 10-, and 15-min interval respectively in cross-correlated effect. The returns in cross-correlated effect seem to be higher than those of auto-correlated effect. A one-tail Z-test has been performed. The P-values reported in Panel A are 0.3125, 0.9437, 0.5555 under 5-, 10-, and 15-min interval respectively in auto-correlated effect, and 0.0984, 0.7771, and 0.5640 under 5-, 10-, and 10-min interval respectively in cross-correlated effect. At 5% significant level, there is no significant positive profit by executing the trading strategy.

We also perform paired-t test to test whether the trading strategy can beat the market, that is, original open-to-close return. From Panel B, we find that the one-tail P-values are 0.1007, 0.1241, and 0.0826 under 5-, 10-, and 15-min interval respectively in auto-correlated effect, and 0.0362, 0.0004, and 0.0071 under 5-, 10-, and 15-min interval respectively in cross-correlated effect. We can't argue the trading strategy beat the market in either auto-correlated or cross-correlated effect.

In addition, we check whether the trading strategy makes significantly difference among 5-, 10-, and 15-min intervals. Panel C shows that the returns of strategy under 5-min interval are significantly better than those under 10-min interval in both auto-correlated effect and cross-correlated effect situation, but insignificant difference.

To sum up, we find that imbalance-based trading strategy is not able to beat the market in commercial banks in financial crisis, which implies that there exists an efficient market. Moreover, we get the result that 5-min returns of strategy are significantly better than 10-min returns, and this is consistent with our previous empirical results of dynamic return-order imbalance

Table 5: Trading profit

Panel A: Returns compared with zero

$$1.\ \begin{cases} H_0: \mu_i \leq 0 \\ H_1: \mu_i > 0 \end{cases}$$

Where μ_i is the return of the trading strategy, *i* denotes 5-, 10-, and 15-min interval

	5 min return of strategy	10 min return of strategy	15 min return of strategy
Overall effect			
P-value	0.0884	0.9147	0.5785
Auto correlated effect			
P-value	0.3125	0.9437	0.5555
Cross-correlated effect			
P-value	0.0984	0.7771	0.5640

Panel B: Returns compared with returns of buy-and-hold strategy

$$2.\ \begin{cases} H_0: \mu_i \geq \mu_0 \\ H_1: \mu_i < \mu_0 \end{cases}$$

Where μ_i is the return of the trading strategy, μ_0 is the original open-to-close return

	Original open-to-close return	5 min return	10 min return	15 min return
Overall effect				
Mean	1.46%	0.46%	−0.43%	−0.06%
P-value		0.0136	0.0001	0.0023
Auto correlated effect				
Mean	1.54%	0.38%	−-0.85%	−0.05%
P-value		0.1007	0.0124	0.0826
Cross-correlated effect				
Mean	1.43%	0.49%	−0.29%	−0.06%
P-value		0.0362	0.0005	0.0071

Panel C: Differences in returns among the three intervals

$$3.\ \begin{cases} H_0: \mu_i = \mu_j \\ H_1: \mu_i \neq \mu_j \end{cases}$$

Where μ_i is return of the trading strategy, *i, j* denotes 5, 10, and 15 min intervals, *i≠j*

	5 min and 10 min	5 min and 15 min	10 min and 15 min
Overall effect			
P-value	0.0006	0.1002	0.1071
Auto correlated effect			
P-value	0.0366	0.5896	0.1322
Cross-correlated effect			
P-value	0.0071	0.0988	0.3651

GARCH relation, which shows a decreasing trend from 5-min to 10-min interval. Thus, market makers do have the capability of mitigating volatility through inventory adjustments, even in financial crisis.

6. DYNAMIC CAUSAL RELATIONSHIP IN EXPLAINING THE RETURN-ORDER IMBALANCE RELATIONSHIP

Finally, in order to explain the story behind an imbalance-based trading strategy, we employ a nested causality to explore the dynamic causal relationship between returns and order imbalances. According to Chen and Wu (1999), we define four relationships between two random variables, x_1 and x_2, in terms of constraints on the conditional variances of $x_{1(T+1)}$ and $x_{2(T+1)}$ based on various available information sets, where $x_i=(x_{i1}, x_{i2}, ., x_{iT})$, i=1, 2, are vectors of observations up to time period T.

Definition 1: Independency, $x_1 \wedge x_2$:

x_1 and x_2 are independent if:

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

And

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

Definition 2: Contemporaneous relationship, x_1 <–> x_2:

x_1 and x_2 are contemporaneously related if:

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

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

And

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

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

Definition 3: Unidirectional relationship, x_1=>x_2:

There is a unidirectional relationship from x_1 to x_2 if:

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

And

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

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

There is a feedback relationship between x_1 and x_2 if

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

And

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

To explore the dynamic relationship within a bi-variate system, we form the five statistical hypotheses in Table 6 where the necessary and sufficient conditions corresponding to each hypothesis are given in terms of constraints on the parameter values of the vector autoregression (VAR) model. To determine whether there exists a specific causal relationship, we use a systematic multiple hypotheses testing method.

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

Unlike the traditional pair-wise 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=>x_2, we need to establish that x_1<≠x_2 and to reject that x_1≠>x_2. To conclude that x_1<–>x_2, we need to establish that x_1<≠x_2 as well as x_1≠>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 the conclusion that a dynamic relationship exists. The following presents an

Table 6: Hypotheses on the dynamic relationship of a bivariate system

Hypotheses	The VAR test
H_1: x_1^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≠>x_2	$\varphi_{21}(L)=0$
H_3*: x_2≠>x_1	$\varphi_{12}(L)=0$
H_4: x_1<=>x_2	$\varphi_{12}(L)^* \varphi_{21}(L) \neq 0$
H_5: x_1≠>>x_2	$\varphi_{21}(L)=0$, and $\sigma_{12}=\sigma_{21}=0$
H_6: x_2≠>>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 may be expressed as: $\begin{bmatrix} \varphi_{11}(L) & \varphi_{12}(L) \\ \varphi_{21}(L) & \varphi_{22}(L) \end{bmatrix} \begin{bmatrix} \mathbf{x}_{1t} \\ \mathbf{x}_{2t} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$ where x_{1t} and x_{2t} are mean adjusted variables. The first and second moments of the error structure, $\underset{\sim}{\varepsilon_{\mathbf{t}}} = (\varepsilon_{1t}, \varepsilon_{2t})'$ are that, $\mathbf{E}(\underset{\sim}{\varepsilon_{\mathbf{t}}}) = 0$ and $\mathbf{E}(\underset{\sim}{\varepsilon_{\mathbf{t}}} \underset{\sim}{\varepsilon_{\mathbf{t+k}}}) = 0$ for $k \neq 0$ and $\mathbf{E}(\underset{\sim}{\varepsilon_{\mathbf{t}}} \underset{\sim}{\varepsilon_{\mathbf{t+k}}}) = \Sigma$ for $k=0$, where $\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$

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 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-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.

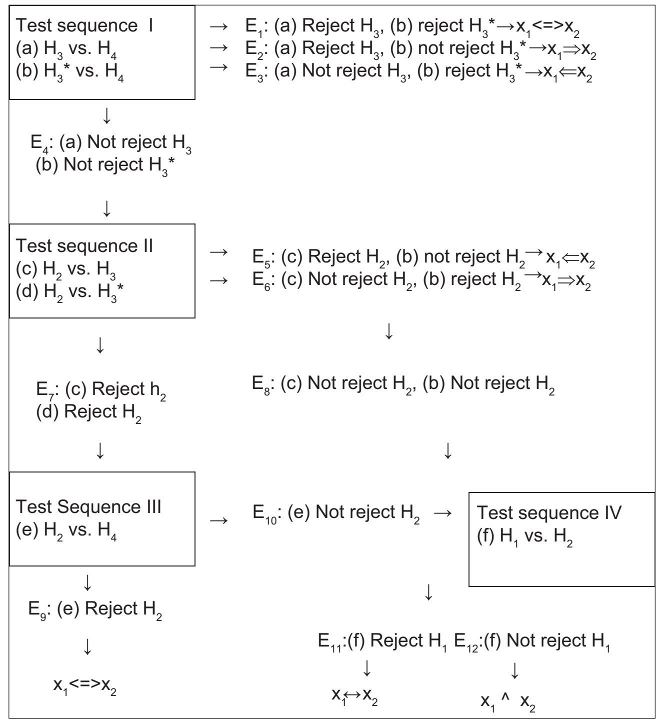
To explore the dynamic return-order imbalance relationship during the price formation process, we employ a nested causality approach. In order to investigate the dynamic relationship between two variables, we impose the constraints in the upper panel of Table 6 for the VAR model. In Table 7, we present the empirical results of the tests of the hypotheses for the dynamic relationship in Table 2. For the entire sample, we show that the unidirectional relationship from returns to order imbalances is 0.00% of the sample firms for the entire sample, while the unidirectional relationship from order imbalances to returns is 50.00%. The percentage of firms that fall into the independent category is 0.00%. Moreover, 25.00% of firms exhibit a contemporaneous relationship between returns and order imbalances. Finally, 25.00% 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 larger than that exhibiting such a unidirectional relationship from returns to order imbalances, suggesting that order imbalances constitute a better indicator for predicting future returns. This finding is consistent with many articles, which document that future daily returns could be predicted by daily order imbalances (Brown et al., 1997; Chordia and Subrahmanyam, 2004). In addition, the percentage of firms exhibiting a contemporaneous relationship is 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.

7. CONCLUSION

In recent years, there has been a dramatic proliferation of research concerned with market efficiency while recent global financial crisis has led to renewed criticism of the hypothesis. The main purpose of our study is to investigate market efficiency in financial crisis. In our study, we investigate the relation among the intraday stock return, volatility and order imbalances of commercial banks during financial crisis.

We collect the sample of the major U.S. commercial bank stocks 4 days before and after Lehman Brothers bankruptcy. First, we use a multiple-regression by contemporaneous returns and five lagged order imbalances to examine the unconditional lagged return- order imbalance OLS relation. We find that there is no

Figure 1: Test flow chart of a multiple hypothesis testing procedure



Five groups of dynamic relationship are identified: Independency ($\wedge$) the contemporaneous relationship ($\leftrightarrow$) the 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 the 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 $x_1 \neq> x_2$. 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 regarding the dynamic relationship can be drawn

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

Trade size	$x_1 \wedge x_2$	$x_1 <-> x_2$	$x_1 \Rightarrow x_2$	$x_1 \Leftarrow x_2$	$x_1 <=> x_2$
All trade size	0.00%	25.00%	0.00%	50.00%	25.00%

The causal relationships are defined as follows: 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 $\sigma_{12}=\sigma_{21}=0$. The percentage explained by each dynamic relationship is based on a 5% significance level of tests

significantly positive relation between current stock returns and lagged-one order imbalances, which is inconsistent with Chordia and Subrahmanyam (2004).

We examine both auto-correlated and cross-correlated effect. In auto-correlated effect, a negative relation between current returns and order imbalances is documented. It implies that market makers have a better capability to adjust inventory. Second, we examine conditional returns-order imbalances relation. The empirical results show that contemporaneous order imbalances are significantly positive at all significant levels and under all time intervals in overall, auto-correlated, and cross-correlated effect, while most of the coefficients of lagged-one imbalances turn to be significantly negative, which is consistent with Chordia and Subrahmanyam (2004). We also employ a time varying GARCH model to investigate return-order imbalance relation. We confirm the important rile of volatility in return-order imbalance relation.

Moreover, the relation between price volatility and order imbalance is also an important issue in our study. We observe that the proportion of significantly positive or negative coefficients of order imbalances is not as large as we expect. The low connection between order imbalances and price volatility could be explained that market makers have good control on commercial banks' price volatility. Finally, we form an intraday imbalance-based trading strategy to test market efficiency. From the empirical results, our trading strategy is not able to beat the market. It implies an efficient market in commercial banks. A nested causality testing confirms the results.

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