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Illiquid Trades on Investment Banks in Financial Crisis

Han-ching Huang[1], Yong-chern Su[1] and Hsin-Pei Tu[1]

Abstract

This paper examine the unconditional lagged return-order imbalance relation and find that either before or after the financial crisis, the correlation between returns and lagged-one order imbalance is both positive. We also show that before the financial crisis, contemporaneous order imbalances are significant and positive, while some of the coefficients of lagged-one imbalances turn to be significantly negative. After the financial crisis, however, the signs of a positive relationship between contemporaneous order imbalances and returns become weaker, but the lagged-one order balances coefficients become stronger. In GARCH model, our results are significant at 1% level, and order imbalance clearly has a higher predictive power after the financial crisis than before the financial crisis, even the market liquidity is less after the financial crisis. Although our results show that the explanatory power of order imbalance towards volatility may be greater after the financial crisis, the proportion of significantly positive or negative coefficients of order imbalances is less than we expect. We construct an imbalance-based trading strategy and find no significant positive returns before and after the financial crisis. Thus, we cannot earn positive returns by using the strategy during pre-crisis and post-crisis periods.

JEL classification numbers: G11, G14
Keywords: illiquid trade, investment bank, financial crisis

[1] Chung Yuan Christian University, Taiwan

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1 Introduction

Stock liquidity and its effect on market return have been widely discussed in the finance field. According to the concept that traders can gain abnormal return by inside information, market efficiency plays an important role to govern the probability of this phenomenon. For highly liquid equity markets like NYSE (New York Stock Exchange) and NASDAQ, it's hardly to pursue abnormal profits for traders whose trading strategies are constructed by the relationship between trading volumes and price trends [19], [16]. This can be attributed to the strong liquidity of NYSE market which is enough of keeping market trading efficiency, forbidding traders to gain abnormal returns [12], [22].

Although NYSE has a strong form of market efficiency, we still doubt whether this efficiency can maintain under financial crisis that have severe destructions on liquidity and price. In addition to examine the market efficiency under shortage of liquidity during the financial crisis, we also concern whether there is any speculative opportunity to gain returns by taking advantage of the anomaly.

We apply the Lee and Ready [20] trade assignment algorithm to determine the direction of each order and compile these order data into daily order imbalances. We use regression to test both contemporaneous as well as lagged relations between returns and order imbalances. By observing the statistical significance of both contemporaneous and lagged order imbalances with daily stock returns, we trace the market makers for dynamical reactions to the price pressure caused by large traders. GARCH (1, 1) model is also employed to explore the impacts of order imbalance on returns. Finally, we form several trading strategies that leverage our information about order imbalances to examine whether these strategies enable investors to realize abnormal profits.

Main findings of this paper are as follows. First, we adopt a multiple-regression model with contemporaneous returns and five lagged order imbalances to examine the unconditional lagged return-order imbalance relation and find that either before or after the financial crisis, the correlation between returns and lagged-one order imbalance is both positive. Second, we also show that before the financial crisis, contemporaneous order imbalances are significant and positive, while some of the coefficients of lagged-one imbalances turn to be significantly negative. After the financial crisis, however, the signs of a positive relationship between contemporaneous order imbalances and returns become weaker, but the lagged-one order balances coefficients become stronger. Third, in GARCH model, our results are significant at 1% level, and order imbalance clearly has a higher predictive power after the financial crisis than before the financial crisis, even the market liquidity is less after the financial crisis. Four, although our results show that the explanatory power of order imbalance towards volatility may be greater after the financial crisis, the proportion of significantly positive or negative coefficients of order imbalances is less than we expect. Five, we construct a daily trading strategy based on the sign of large order imbalances. We find no significant positive returns before and after the financial crisis. Thus, our imbalance-based trading strategy is not profitable, and we cannot earn positive returns by using the strategy during pre-crisis and post-crisis periods. Last, we find that the imbalance-based strategy result a better return compared with buy-and-hold trading strategy after the financial crisis. The returns after crisis are larger than those before crisis, implying that order imbalances have a better predictive power when the market is illiquid.

The remainder of this paper proceeds as follows. In Section 2, we review the related literature. Section 3 describes the data source and characteristics of our data, accompanied by our methodology for pre-processing them. Afterward we present our empirical findings in Section 4. In Section 5, we provide a summary of our obtained results, and discuss the conclusions that we have reached.

2 Literature Review

Since Eugene Fama developed efficient market hypothesis in early 1960s, lots of researchers study on market efficiency. The efficient-market hypothesis suggests that prices fully reflect all available information at any given time namely no investor can earn excess return by any trading strategy, which was generally accepted before 1990s. However, later research discovered that different kinds of market anomalies exist in the market, such as weekend effect, January effect, size effect, etc. Psychology theories were later used to explain these anomalies, in another word, behavioral finance came into play.

Amihud and Mendelson [1] explore the effect of the bid-ask spread on asset pricing with considerations of liquidity, assuming that investors with different expected holding periods trade assets with different relative spreads. They concluded that market-observed expected return is an increasing and concave function of the spread. Since the strategic behavior of liquidity traders and informed traders, Admati and Pfleiderer [2] claimed the intraday concentrated-trading patterns arise endogenously, liquidity traders tend to trade more concentrated in periods closer to the realization of their demands and informed traders trade more actively when liquidity trading is concentrated.

Brennan, Jegadeesh and Swaminathan [5] found out that even with the same size, returns on portfolios of firms followed by more analysts are better than those followed by fewer. Moreover, firms followed by more analysts tend to respond more rapidly to market returns than do firms followed by fewer analysts. Brennan and Subrahmanyam (1995) further studied the relation between number of analysts following the security and the estimated adverse selection cost of transacting in the security, finding that more analyst following tends to reduce adverse selection costs.

Quoted bid-ask spread was used in previous studies for measuring illiquidity and find the quoted bid-ask spread is a noisy measure of illiquidity. Though relation between required rates of return and the measures of illiquidity they used is not significant, Brennan and Subrahmanyam [7] examine the relations between monthly stock returns and illiquidity by using Fama and French [15] factors to adjust for risk, and measure illiquidity by using intraday trading data. Brennan, Chordia and Subrahmanyam [8] further examine the relations between stock returns, measures of risk, and other non-risk security characteristics like size, book-to-market ratio, stock price and its lagged return, and dividend yield. After accounting for Fama–MacBeth-type regressions using risk adjusted returns provide evidence of return momentum, size, and book-to-market effects, they find a significant and negative relation between returns and trading volume. Moreover, when momentum and trading volume effects persist, the analysis repeatedly using the Fama and French [15] factors will find that size and book-to-market effects are attenuated.

Jacoby, Fowler and Gottesman [17] develop a CAPM-based model to examine that whether true measure of systematic risk considering liquidity costs is based on net (after bid–ask spread) returns and the relations between expected returns and future spread costs, which is concluded to be positive and convex.

Amihud [3] demonstrates that illiquidity affects more strongly for small firms stocks, applying the average daily ratio of absolute stock return to dollar volume as the illiquidity measure, thus explaining for small firm effects. The study also find that the impact of market illiquidity on stock excess return can confirm the existence of illiquidity premium and helps explain the equity premium puzzle.

Market order imbalances defined as aggregated daily market purchase order minus sell order shows to be positive autocorrelated by Chordia [10]. Order imbalances initiated by buyer will likely to be followed by several days of aggregate buyer-initiate order imbalance, and vice versa. Traders may herd, or split large order over time due to positively autocorrelated order imbalance implying that investors continue to buy or to sell for a period.

Chordia, Roll and Subrahmanyam [10] use the aggregate daily order imbalance to measure trading activity and find that order imbalances increase following market declines and vice versa, as if investors are contrarians. In addition, order imbalances in either buy or sell will reduce liquidity. Their study also finds that contemporaneous and lagged order imbalances strongly affect market returns to reverse themselves after high negative imbalance, large negative return days, even after controlling for aggregate volume and liquidity.

P´astor and Stambaugh [21] examine whether market-wide liquidity is a state variable important for asset pricing. They find that expected stock returns are related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity.

Baker and Stein [9] build a model that helps explain why increases in liquidity - such as lower bid-ask spreads, a lower price impact of trade, or higher share turnover - predict lower subsequent returns in both firm-level and aggregate data. They find that aggregate measures of equity issuance and share turnover are highly correlated and yet in a multiple regression, both have incremental predictive power for future equal-weighted market returns. Their study features a class of irrational investors who are underreacted to the information contained in order flow, thereby boosting liquidity. High liquidity unusually sign for the fact that the market currently dominated by these irrational investors is overvalued, due to short-sales constraints.

Eisfeldt [14] forms a model of illiquid long-term risky assets due to adverse selection. The degree of adverse selection and hence the liquidity of these assets is determined endogenously by the amount of trade for reasons other than private information. The study concludes that higher productivity leads to increased liquidity and liquidity magnifies the effects of changes in productivity on investment and volume. High productivity implies that investors initiate larger scale of risky projects which increases the riskiness of their incomes, while riskier incomes induce more sales of claims to high-quality projects, causing liquidity to increase.

Acharya and Pedersen [4] shows if a negative shock to the liquidity a security's is persistent, low contemporaneous returns and high predicted future returns exist. They build an equilibrium asset pricing model with liquidity risk -- the risk arising from unpredictable changes in liquidity over time, and they provide a simple, unified framework for understanding the various channels through which liquidity risk may affect asset prices, In their liquidity-adjusted capital asset pricing model, a security's required return depends on its expected liquidity as well as on the covariances of its own return and liquidity with market return and market liquidity.

Chordia, Huh and Subrahmanyam [11] examine cross-sectional variations in stock trading activity for a comprehensive sample of NYSE/AMEX and Nasdaq stocks over a period. Their theory implies that trading activity depends on the extent of liquidity trading, the mass of informed agents, and dispersion of opinion about the stock's fundamental value. They further postulate that liquidity or noise trading depends both on a stock's visibility and on portfolio rebalancing needs triggered by past stock price performance. They demonstrate that past return is the most significant predictor of stock turnover. Forecast dispersion and systematic risk are also demonstrated important in predicting the cross-section of expected trading activity while they use size, firm age, price, and the book-to-market ratio as proxies for a firm's visibility and the number of analysts following the stock as the mass of informed agents and the analyst forecast dispersion, systematic risk, and firm leverage proxy as divergence of opinion. Stocks that have performed well in a given year experience aggressive buying pressure in the subsequent year, which points to the presence of momentum investing.

Johnson [18] claims that changes in the willingness of agents to accommodate perturbations to their equilibrium portfolio holdings may explain why market liquidity change over time and suggests a natural measure of this flexibility-essentially a shadow elasticity like a shadow price, is well defined whether or not trade actually occurs in the economy. This quantity characterizes the price impact or bid/ask spread that a small trader would experience, and is an endogenous function of the underlying state variables in the economy. The study computes the function for some tractable example models and uncovers a rich variety of predictions about liquidity dynamics that, in some cases, appear consistent with both the levels and covariations observed in the data, and the results have important implications for the pricing and hedging of liquidity risk.

Chordia, Huh and Subrahmanyam [12] estimate illiquidity using structural formulae for a comprehensive sample of stocks. Their empirical results provide evidence of that theory-based estimates of illiquidity are priced in the cross-section of expected stock returns after accounting for risk factors, firm characteristics known to influence returns, and other illiquidity proxies prevalent in the literature. Their method explicitly recognizes the analytic dependence of illiquidity on more primitive drivers such as trading activity and information asymmetry.

Most previous studies about liquidity in asset pricing show that liquidity is important in asset pricing. Some research indicate that order imbalances can be used to investigate the behavior of informed traders and see whether there exists information asymmetry. Thus, we try to investigate the relation among the daily stock return and volatility by order imbalance and the measure of illiquidity which Chordia, Huh and Subrahmanyam [12] use.

3. Data and Methodology

3.1 The Data

We select the stocks that have the highest liquidity before the crisis, just in order to obtain the most rigorous differences before and after the financial crisis. The sample period is during the fifty days before and after the day of Lehman's bankruptcy, Sep 15th 2008. We collect the intraday trading data of bid and ask quotes, trading prices as well as trading size in consolidate quote database from TAQ (Trades and Quotes). We use trading data only within market time (9:30AM to 4:00PM), and ignore trades before the open and after the closing time.

Stock are included or excluded depending on the following criteria:

1. The data of firm can be collected in both the WRDS and TAQ database.
2. The firm is listed on NYSE during the whole 100 day period that we are interested in.
3. The firm's main business is investment banking, which is the main industry to be affected by the financial crisis.
4. We delete transactions within the first 90 seconds after the opening of the market to avoid noise trading.
5. Quotes established and transactions traded before the opening or after the close are excluded.
6. If the quote spread is negative or abnormal during the transaction period, the quote spread is deleted.

It turns out that out of the total 13 firms now listed on the NYSE, only seven of them meet all the criteria above. Therefore, these seven investment banks constitute our sample.

After selecting the sample that meets our criteria, we calculate the daily order imbalances and daily stock return for each firm. We define each transaction as either buyer-initiated or seller-initiated by using trade assignment algorithm suggest by Lee and Ready [20]. The trade is classified as buyer(seller)-initiated if the actual transaction price is greater(less) than the mid-point of the bid and ask price. The tick test is executed when the trade price is exactly at the midpoint of the bid and ask price. The classification as buyer (seller)-initiated declares when the last price is positive (negative). According to Chordia and Subrahmanyam [10], we define order imbalance as trading size of buyer-initiated minus trading size of seller-initiated. Finally, we calculate daily return and order imbalances for the entire 100 day period.

Based on the criteria mentioned above, we choose stocks of major investment banks in the United States, including Citi Group (NYSE: C), Bank of America (NYSE: BOA), J. P. Morgan Chase & Company (NYSE: JPM), Goldman Sachs (NYSE: GS), Morgan Stanley (NYSE: MS), Jefferies Group Inc. (NYSE: JEF), and Raymond James Financial Inc. (NYSE: RJF). The descriptive statistics of our sample stocks are presented in Table 1. The mean of open-to-close return is -0.11%, with a median of -0.54%. The standard deviation of return is 8.67%, with a maximum of 86.98% and a minimum of -26.41%. The skewness of daily return is 1.9849 and the kurtosis is 16.8553. During the pre-crisis period, the mean of open-to-close return is 0.16%, with a median of -0.12%. The standard deviation of return is 5.15%, with a maximum of 22.41% and a minimum of -21.31%. The skewness of daily return is 0.5008 and the kurtosis is 2.4892. During the post-crisis period, the mean of open-to-close return is -0.41%, with a median of -1.84%. The standard deviation of return is 11.37%, with a maximum of 86.98% and a minimum of -26.41%. The skewness of daily return is 1.8869 and the kurtosis is 11.5797.

Table 1: Descriptive Statistics of Selected Stocks' Daily Return

Panel A: All Period

Stock	Mean	Median	Standard Deviation	Maximum	Minimum	Skewness	Kurtosis
C	-0.20%	-0.55%	10.24%	57.82%	-26.41%	1.6860	9.4862
BOA	0.00%	-0.37%	8.60%	27.20%	-26.23%	0.3157	1.4068
JPM	0.16%	-0.18%	6.82%	21.39%	-17.88%	0.3724	0.7731
GS	-0.56%	-0.74%	6.50%	26.47%	-13.92%	1.3015	4.5768
MS	-0.21%	-0.05%	12.47%	86.98%	-25.89%	3.2511	22.7827
JEF	-0.03%	-0.49%	7.00%	23.83%	-16.89%	0.5822	1.0722
RJF	0.10%	-0.74%	7.63%	24.63%	-19.48%	0.7310	1.6498
Total	-0.11%	-0.54%	8.67%	86.98%	-26.41%	1.9849	16.8553

Panel B: Pre-Crisis Period

Stock	Mean	Median	Standard Deviation	Maximum	Minimum	Skewness	Kurtosis
C	-0.03%	-0.12%	5.11%	13.12%	-15.14%	-0.2293	0.7958
BOA	0.66%	1.01%	7.26%	22.41%	-21.31%	0.3337	1.8857
JPM	0.46%	0.67%	5.03%	15.86%	-10.13%	0.6704	1.2639
GS	-0.46%	-0.55%	3.37%	9.54%	-12.13%	-0.2507	2.6381
MS	-0.35%	-0.05%	4.75%	13.06%	-13.54%	-0.0316	1.0453
JEF	0.45%	-0.23%	5.65%	20.09%	-9.34%	1.1637	2.4507
RJF	0.35%	-0.37%	4.18%	11.70%	-7.84%	0.6542	0.6783
Total	0.16%	-0.12%	5.15%	22.41%	-21.31%	0.5008	2.4892

Panel C: Post-Crisis Period

Stock	Mean	Median	Standard Deviation	Maximum	Minimum	Skewness	Kurtosis
C	-0.38%	-2.64%	13.68%	57.82%	-26.41%	1.5180	5.3669
BOA	-0.67%	-2.04%	9.80%	27.20%	-26.23%	0.4018	1.0511
JPM	-0.15%	-1.30%	8.30%	21.39%	-17.88%	0.3511	0.0355
GS	-0.65%	-1.97%	8.64%	26.47%	-13.92%	1.1982	2.0598
MS	-0.06%	0.59%	17.14%	86.98%	-25.89%	2.5777	12.3621
JEF	-0.52%	-1.45%	8.18%	23.83%	-16.89%	0.4661	0.3242
RJF	-0.15%	-1.92%	10.04%	24.63%	-19.48%	0.6846	0.1848
Total	-0.41%	-1.84%	11.37%	86.98%	-26.41%	1.8869	11.5797

3.2 Methodology

3.2.1 Unconditional Lagged Return-Order Imbalances OLS Model

In order to know the prediction power of lagged order imbalances, we adopt multi-regression model to explore the impact of five lagged order imbalances on current stock returns during the pre-crisis and post-crisis periods. The linear regression model is as followed:

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

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

If the coefficient of first lagged order imbalance is positive and significant, we can infer that the order imbalances have positively predictive power on future returns. Therefore, we can use order imbalances to form some profitable trading strategies. Moreover, we can analyze the impacts of the 2008 financial crisis on market efficiency by examining the role of order imbalance in determining returns.

3.2.2 Conditional Contemporaneous Return-Order Imbalances OLS Model

In this section, we use a multiple-regression model with contemporaneous and four lagged order imbalances to examine the conditional lagged return-order imbalance OLS relation during the pre-crisis and post-crisis periods. The linear regression model is as followed:

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

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

According to Chordia, Huh, and Subrahmanyam [12], 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 over-weighting of market makers. Moreover, we can analyze the impacts of the 2008 financial crisis on market efficiency by examining the statistical significance of order imbalance's role in determining returns.

3.2.3 Dynamic Return-Order Imbalance GARCH (1, 1) Model

We adopt GARCH (1,1) model, which can catch the time-variant property of price series, to enhance preciseness of analyzing the data. The following model is used to examine the dynamic relation between returns and order imbalances during the pre-crisis and post-crisis periods:

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

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

$$h_t = A + Bh_{t-1} + C\varepsilon_{t-1}^2 \tag{3}$$

where R_t is the return at time t, and is defined as ln (Pt)-ln(Pt-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, and Ω_{t-1} is the information set in at time t-1.

We examine the coefficient β to explore whether there exists significant effect of the order imbalances on contemporaneous returns. In addition, we can recognize whether the GARCH (1,1) model is able to capture the time variant property by observing the significance of coefficient B.

3.2.4 Dynamic Return-Order Imbalance GARCH (1, 1) Model

We adopt GARCH (1, 1) model to investigate whether a larger order imbalance leads to a larger price volatility during the pre-crisis and post-crisis periods:

$$R_t = \alpha + \varepsilon_t$$

$$\varepsilon_t | \Omega_t \sim N(0, h_t)$$

$$h_t = A + Bh_{t-1} + C\varepsilon_{t-1}^2 + \gamma OI_t \quad (4)$$

where R_t is the return at time t, and is defined as ln (Pt)-ln(Pt-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.

We use the coefficient γ to examine the relations between OI and volatility.

3.2.5 Liquidity Measurement

We use liquidity estimation model suggested by Chordia, Huh and Subrahmanyam [12] to assess market's liquidity during pre-crisis and post-crisis periods.

The liquidity measure is:

$$L = \frac{\lambda_i}{P_i} \quad (5)$$

where λ_i is the coefficient of lag one order imbalance in unconditional return-order imbalance OLS model at period *i*, P_i is the average market close prices of samples in unconditional return-order imbalance OLS model at period *i*.

4 Empirical Results

4.1 Unconditional Lagged Return-Order Imbalances Relation

We examine the unconditional lagged return-order imbalance relation through using a multiple-regression model with current returns and five lagged order imbalances. We explore whether lagged order imbalances bear a positive predictive relation to current returns of investment banks.

Panel A of Table 2 presents the empirical results before financial crisis and shows that the average coefficient of lagged-one order imbalance is positive and the percentage of lagged-one order imbalances is 42.86%. At 5% significant level, the ratio of positive and significant coefficients of lagged-one order imbalance is

14.29%, and the ratio of negative and significant coefficient is 0.0%. Panel B of Table 2 shows that after the financial crisis, the average coefficient of lagged-one order imbalance is positive, and the percentage of positive lagged-one order imbalances is 85.71%. At the 5% level, the ratio of positive and significant coefficients is 0.0%, and the ratio of negative and significant coefficient is 0.0%.

Table 2: The Unconditional Lagged Return-Order Imbalance Relation

Panel A: Pre-Crisis Period

	Average	Positive	Positive and significant	Negative and significant
OI_{t-1}	1.82E-06	42.86%	14.29%	0.00%
OI_{t-2}	-1.40E-06	28.57%	0.00%	0.00%
OI_{t-3}	1.44E-06	71.43%	0.00%	0.00%
OI_{t-4}	6.70E-07	71.43%	0.00%	0.00%
OI_{t-5}	1.48E-06	71.43%	14.29%	0.00%

Panel B: Post-Crisis Period

	Average	Positive	Positive and significant	Negative and significant
OI_{t-1}	4.12E-06	85.71%	0.00%	0.00%
OI_{t-2}	3.82E-06	57.14%	0.00%	0.00%
OI_{t-3}	-5.25E-06	42.86%	0.00%	0.00%
OI_{t-4}	-1.21E-06	14.29%	0.00%	0.00%
OI_{t-5}	2.66E-06	42.86%	0.00%	0.00%

Note: "Significant" denotes significance at the 5% level.

Comparing the results before and after financial crisis, we find that the percentage of positive and significant for lagged-one order imbalance is higher than the percentage of negative and significant during the pre-crisis period. The percentage of positive and significant of lagged-one order imbalance is still higher than the percentage of negative and significant during the post-crisis period during the pre-crisis period. Moreover, the percentages of significant coefficients are less than those in Chordia and Subrahmanyam [13], representing that the predictive power in our paper is less strong than that in Chordia and Subrahmanyam [13].

Explanations of our findings are as follows. When market makers face the imbalance pressure, they provide efforts for liquidity to eliminate the pressure of the imbalance order. When a large sell-initiated order enters the market, market makers tend to raise quote price and cause the positive return. Negative relation between lagged-one imbalance and returns hence occurs when the market makers have enough stocks to control the price. As a result, some negative relations exist before the financial crisis. Even the difference is less, the percentage of positive and significant lagged-one order imbalance is still higher than that of negative and significant during the post-crisis period.

4.2 Conditional Contemporaneous Return-Order Imbalances Relation

Panel A of Table 3 presents that during the pre-crisis period, the average coefficient of contemporaneous order imbalance is positive and the percentage of positive contemporaneous order imbalances is 71.43%. At the 5% level, the ratio of positive and significant coefficients of contemporaneous order imbalance is 57.14%, and the ratio of negative and significant coefficient is 0.0%.

Panel B of Table 3 shows that during the post-crisis period, the average coefficient of contemporaneous order imbalance is positive and the percentage of positive contemporaneous order imbalances is 100.0%. At the 5% level, the ratio of positive and significant coefficients of contemporaneous order imbalance is 71.43% and the ratio of negative and significant coefficient is 0.0%.

Our empirical results show that most of the coefficients of contemporaneous order imbalances are significantly positive, while the percentage of negative coefficients of lagged-one imbalances increase, which is generally consistent with Chordia and Subrahmanyam [13].

Table 3: The Conditional Lagged Return-Order Imbalance OLS Relation
Panel A: Pre-Crisis Period

	Average	Positive	Positive and significant	Negative and significant
OI_{t-1}	8.43E-06	71.43%	57.14%	0.00%
OI_{t-2}	1.51E-06	42.86%	14.29%	0.00%
OI_{t-3}	-3.52E-07	28.57%	0.00%	0.00%
OI_{t-4}	4.74E-07	57.14%	0.00%	0.00%
OI_{t-5}	3.14E-07	57.14%	0.00%	0.00%

Panel B: Post-Crisis Period

	Average	Positive	Positive and significant	Negative and significant
OI_{t-1}	5.05E-06	100.00%	71.43%	0.00%
OI_{t-2}	3.86E-06	85.71%	0.00%	0.00%
OI_{t-3}	3.54E-06	71.43%	0.00%	0.00%
OI_{t-4}	-5.45E-06	42.86%	0.00%	0.00%
OI_{t-5}	2.83E-07	42.86%	0.00%	14.29%

Note: "Significant" denotes significance at the 5% level.

4.3 Dynamic Return -Order Imbalance GARCH (1, 1) Relation

Since the stock prices are autocorrelated and the variances of the samples are not as constant, we adopt GARCH (1,1) model to seize the time-variant property of price series. The detail results are summarized in Table 4.

The results in Table 4 are similar with those in conditional OLS regression model. The average coefficient of contemporaneous order imbalance is 5.23E-06 before financial crisis, while the average coefficient increases to 8.67E-06 after crisis. The percentage of positive coefficients is 100% before crisis, and the percentage of positive coefficients is 100% after crisis. At the 5% level, the proportion of significantly positive β is 71.43% before crisis and 85.71% after crisis.

Although the results in GARCH (1,1) model are similar with those in OLS model, the explaining power of order imbalance in GARCH (1,1) model is higher than that in the OLS regression model. When OLS regression model is used, we assume the variance is constant over time. While this assumption is not appropriate in the real market, the stock prices do not fluctuate constantly. Hence, we further use GARCH (1,1) model instead of OLS regression model to find more precise and reliable results.

Table 4: Dynamic Return-Order Imbalance GARCH (1,1) Relation

Panel A: Results

Time Interval	Return	OI	B	Significance of B	β	Significance of β
Before Crisis	C	C	0.1282	0.2809	2.81E-06	4.0945
After Crisis	C	C	0.7210	1.8499	4.91E-06	4.0837
Before Crisis	BOA	BOA	0.0768	0.5281	3.80E-06	7.7130
After Crisis	BOA	BOA	0.0312	3016.9500	2.65E-06	3.6670
Before Crisis	JPM	JPM	0.0000	0.0000	7.86E-07	0.8903
After Crisis	JPM	JPM	0.0000	0.0000	3.71E-06	8.4677
Before Crisis	GS	GS	0.0000	0.0000	4.67E-06	1.9415
After Crisis	GS	GS	0.0000	0.0000	6.90E-06	1.9055
Before Crisis	MS	MS	0.1241	0.3437	1.04E-05	3.6332
After Crisis	MS	MS	0.4578	4.3537	2.98E-05	9.5778
Before Crisis	JEF	JEF	0.0000	0.0000	4.82E-06	5.3439
After Crisis	JEF	JEF	0.6337	0.8841	2.52E-06	2.1675
Before Crisis	RJF	RJF	0.4589	13175.3000	9.32E-06	4.6954
After Crisis	RJF	RJF	0.9584	2.7913	1.02E-05	2.6182

Panel B Summary

β	Average	positive	Positive and Significant	Negative and Significant	Total
Pre Crisis	5.23E-06	100.00%	71.43%	0.00%	71.43%
After Crisis	8.67E-06	100.00%	85.71%	0.00%	85.71%

Note: “Significant” denotes significance at the 5% level.

4.4 Dynamic Return -Order Imbalance GARCH (1, 1) Relation

In this section, we test the relations between price volatility and order imbalance, and the relations are expected be positive correlated. In other words, the larger order imbalances are associated with the larger price volatility. The empirical results are summarized in Table 5.

Table 5 shows that the proportions of significantly positive or negative coefficients of order imbalances before the financial crisis are as what we expected. That is, the impact of order imbalance on volatility is strong. Nonetheless, after the financial crisis, the coefficients are not as significant as those prior to the financial crisis. Before the crisis, the average coefficient of order imbalance is 52.21, whereas after the crisis, the average coefficient is only 0.106.

Before the financial crisis, at the 5% level, the percentage of positive and significant coefficients is 42.86% and 57.14% for negative one. After the financial crisis, at the 5% level, the percentage of positive and significant coefficients is still 42.86% and 57.14% for negative one.

The weaken correlation between order imbalances and price volatility could be explained as follows. The market makers have good control on investment banks' price volatility, indicating that the market makers have good inventory adjustment mechanism. Nevertheless, the above situation exists only after the financial crisis.

When liquidity is scarce, an offer provided by a market maker can have a weighting effect on the stock price. Thus, traders can have more transparent view of the covert actions of market makers by observing the order imbalance.

Table 5 Dynamic Volitility-Order Imbalance GARCH (1,1) Relation
Panel A: Results

Time Interval	Return	OI	B	Significance of B	γ	Significance of γ
Before Crisis	C	C	0.9003	5.98E+30	-6.00E-05	-3.5756
After Crisis	C	C	0.4524	1.41E+21	0.0680	3.6064
Before Crisis	BOA	BOA	0.2336	5.53E+22	-0.0019	-3.6404
After Crisis	BOA	BOA	0.3202	4.11E+26	0.0007	3.5914
Before Crisis	JPM	JPM	0.5239	4.23E+21	0.1652	3.6401
After Crisis	JPM	JPM	0.0001	1.44E+23	-1.70E-06	-1955.6700
Before Crisis	GS	GS	1.0000	108.482	-365.613	-3.6261
After Crisis	GS	GS	0.5419	2.19E+22	-7.80E-05	-6.4371
Before Crisis	MS	MS	0.8951	4.18E+23	-0.0012	-3.6396
After Crisis	MS	MS	0.0000	2.49E+18	-0.0002	-5.3375
Before Crisis	JEF	JEF	0.8219	1.47E+26	5.79E-05	3.6411
After Crisis	JEF	JEF	0.8999	3.97E+25	0.0153	3.6035
Before Crisis	RJF	RJF	0.1099	2.56E+24	0.0018	4.4793
After Crisis	RJF	RJF	0.6357	4.82E+25	-0.0097	-3.6057

Panel B: Summary

γ	Average	positive	Positive and Significant	Negative and Significant
Pre Crisis	52.207	42.86%	42.86%	57.14%
After Crisis	0.010581	42.86%	42.86%	57.14%

Note: "Significant" denotes significance at the 5% level.

Since market makers don't need to adjust quote price largely to stabilize the market, investors can't influence the stock continuously. However, because the increase in explanatory power of order imbalance is only mediocre in our findings, implying that market makers are still able to stable price volatility when facing the stock's own unexpected shocks, especially after the financial crisis.

4.5 Liquidity Measurement

In this section, we measure the difference of liquidity of investment banks' stocks during financial pre-crisis and post-crisis periods. Based on Chordia, Huh, and Subrahmanya [12], we use liquidity measurement proxy to determine the liquidity level. In untabulated tests, the average price-scaled liquidity measure is 3.75E-08 before the financial crisis, while the average price-scaled liquidity measure increases to 1.25E-07 after the financial crisis, indicating that liquidity of the investment banks market is less after financial crisis.

4.6 Trading Strategy

We try to develop a trading strategy based on the sign of large order imbalances to examine whether the trading strategy can beat the market. Our strategy is as follows. First, we adopt 10% of the largest order imbalances for the pre-crisis and post-crisis periods. Then we purchase the stock at the beginning of next trading day when the first corresponding large positive order imbalance appears. Finally we sell the stock until the first corresponding large negative order imbalance appears. We show the detail results in Panel A of Table 6 and hypothesis test in Panels B, C and D.

Based on our strategy in the pre-crisis period, we can earn a daily return of 0.61%. We adopt one-tail t-test to see whether our trading strategy return is greater than zero. The t-value reported in Panel B is 0.4384, indicating that there is no significant positive profits by executing the trading strategy, even we take 10%

significance level.

After the financial crisis, our strategy faces a daily loss of -3.45%. We also do one-tail t-test to examine whether our trading strategy return is greater than zero. The t-value is -1.3148 under stock-own situation. Thus, our imbalance-based trading strategy is not profitable, and we cannot earn positive returns by using the strategy in the pre-crisis and post-crisis periods.

We also compare the holding period return with and without trading strategy by using paired-t test in Panel C. For one-tailed t-test, the t-value is -8.6281 in the pre-crisis period and 6.9434 in the post-crisis period, implying that the imbalance-based strategy would result in a better return compared with the buy-and-hold strategy after the financial crisis.

Table 6: Trading Strategy

Panel A: Summary of Trading Strategy

Pre-Crisis	Overall Effect	Autocorrelated Effect	Cross-correlated effect
Mean	0.61%	3.04%	0.31%
Standard Deviation	12.62%	13.16%	12.61%
After Crisis			
Mean	-3.45%	-4.49%	-3.32%
Standard Deviation	23.60%	17.27%	24.36%

Panel B: Hypothesis Test of Return-Test 1

Time Interval		Overall Effect	Autocorrelated Effect	Cross-correlated effect
Pre-Crisis	t-value	0.43835	0.693373	0.20941
After-Crisis	t-value	-1.31478	-0.7796	-1.15525

Panel C: Hypothesis Test of Return-Test 2

Time Interval		Overall Effect	Autocorrelated Effect	Cross-correlated effect
Pre-Crisis	t-value	-8.62812	-2.36254	-6.35399
After-Crisis	t-value	6.943404	2.981014	6.465433

Panel D: Hypothesis Test of Return-Test 3

	Overall Effect	Autocorrelated Effect	Cross-correlated effect
t-value	10.94708	5.8382	8.992721

Moreover, we conduct another paired t-test on the difference between the strategy return after crisis and the strategy return before crisis, to explore whether an imbalance-based strategy performs better than the buy-and-hold strategy after the financial crisis in which liquidity is scarce. Panel D shows the t-value is 10.9471, indicating that our imbalance-based strategy performs better in the pre-crisis period than in the post-crisis period. Moreover, the difference between the returns of these two periods is positive, implying that order imbalances have a better predictive power when the market is illiquid. When there is less liquid in the stock market, market makers face greater price pressure by quotes from general traders, suggesting that the proposed system for maintaining market efficiency is deteriorated, thus the predictive power of order imbalance is considerably enhanced.

5 Conclusion

The main purpose of our paper is to examine the effects of liquidity on market efficiency before and after the financial crisis. Since the financial crisis is an extraordinary shock to the financial markets, which interests us regarding the market efficiency hypothesis that how does the sudden and dramatic liquidity lack impair market efficiency. In this paper, we examine the relations between return and order imbalance of investment banks that are most representative before and after Lehman Brothers' bankruptcy, including Citi Group, Bank of America, J. P. Morgan Chase & Company, Goldman Sachs, Morgan Stanley, Jefferies Group Inc., and Raymond James Financial Inc.

We adopt a multiple-regression model with contemporaneous returns and five lagged order imbalances to examine the unconditional lagged return- order imbalance relation, which also examines the prediction power of lagged order imbalances suggested by Chordia and Subrahmanya [13]. Our result is that either before or after the financial crisis, the correlation between returns and lagged-one order imbalance is both positive.

We also use a multiple-regression model to examine the conditional lagged return order imbalance OLS relation regarding current returns contemporaneous and four lagged order imbalances. Our empirical result shows that before the financial crisis, contemporaneous order imbalances are significant and positive, while some of the coefficients of lagged-one imbalances turn to be significantly negative, which is consistent with Chordia and Subrahmanyam [13]. After the financial crisis, however, the signs of a positive relationship between contemporaneous order imbalances and returns become weaker, but the lagged-one order balances coefficients become stronger. We infer that the scarcity of liquidity may affect the mechanism of market makers to overweight current trades as pointed out by Chordia and Subrahmanyam [13]. Because in both unconditional and conditional OLS regressions, the results are insignificant at the 1% level, suggesting that the OLS assumption which the variance is constant may be not appropriate.

As a result, we use GARCH model in order to solve the inappropriateness of OLS regression model assumption and to make our empirical analysis more precisely, since GARCH model can catch the time-variant property of price series. In GARCH model, our results are significant at 1% level, and order imbalance clearly has a higher predictive power after the financial crisis than before the financial crisis, even the market liquidity is less after the financial crisis.

The relation between price volatility and order imbalance is another important issue. Although our results show that the explanatory power of order imbalance towards volatility may be greater after the financial crisis, the proportion of significantly positive or negative coefficients of order imbalances is less than we expect. We infer that the market makers improve their inventory adjustment mechanism more effectively after the financial crisis.

Furthermore, to examine whether the trading strategy can beat the market, we construct a daily trading strategy based on the sign of large order imbalances. We find no significant positive returns before and after the financial crisis. Thus, our imbalance-based trading strategy is not profitable, and we cannot earn positive returns by using the strategy during pre-crisis and post-crisis periods.

We perform a paired t-test to compare the return between imbalance-based and buy-and-hold trading strategies and find that the imbalance-based strategy result a better return compared with buy-and-hold trading strategy after the financial crisis.

We also perform another paired t-test on the returns of imbalance-based strategy both before and after crisis. We find that the returns after crisis are larger than those before crisis, implying that order imbalances have a better predictive power when the market is illiquid. When market makers face greater price pressure by quotes from general traders, the proposed system for maintaining market efficiency is deteriorated, and the predictive power of order imbalance enhances.

In sum, liquidity plays an important role in the aggregate behavior of market makers, particularly in maintaining market efficiency. Our study shows that when the market is less liquid, order imbalances have a greater explanatory power owing to the deteriorated market efficiency. Under liquidity insufficient circumstances, excess market returns exist with the trading strategy that targets the trades with top 10% order imbalances after the financial crisis.

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