An Examination of Informed Trades in China's Stock Market

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A thesis submitted for the degree of Doctor of Philosophy
at XI'AN JIAOTONG- LIVERPOOL UNIVERSITY

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August 2023

Abstract

The thesis mainly examines information-driven trading pattern and trading behavior in China's stock market using intraday high-frequency trading data spanning from 2012 to 2014.

The first empirical chapter studies the intraday trading pattern in China's stock market. We identify generally similar trading phenomena that have been previously reported in other markets, that is, there is a U-shaped intraday pattern of trading volumes. We explore two main research questions associated with this phenomenon: the manifestation of it in other trading-volume-related variables (return, volatility, liquidity and price discovery) and the main driving forces that may explain this phenomenon. By examining high-frequency quote and trading data of all stocks that comprise the CSI300 index, we find that most trading-volume-related variables, such as volatility, liquidity and price discovery, all show similar U-shaped intraday patterns. This reveals that investors' preference to trade during particular time periods (e.g. the opening and ending time of a day) have significant impact on other trading-volume-related variables. To further understand the driving forces behind the observed phenomenon, we also examine the intraday pattern of informed trading behavior and find that the probability of informed trading (PIN) as well as the price discovery (measured by Weighted Price Contribution, WPC) are also much higher at the beginning and ending period than during other time periods of a day. Moreover, a clear intraday momentum effect is also observed. Therefore, we argue that the observed U-shaped intraday trading pattern for the CSI300 stocks is mainly driven by the unbalanced information flow over time within a day.

The second empirical chapter examines the information-driven trades and informed traders' order size strategies in China's stock market. We find the aggregate U-shaped informed trading is not only explained by the time-of-day effect but is also related to the order size strategy, which is shown by intraday variations in the composition of small, medium, and large trades. The evidence of information predictability from early morning to market close and from late afternoon to the next day provides additional insights into the intraday informed trading pattern. We identify the non-negligible price impact (PI) of large trades and propose a modified model, VDPIN-PI, that can better capture the trades with information advantage than the baseline model. Autocorrelation test and information advantage test are applied to ensure the robustness of our main results.

The third empirical chapter focuses on the study of informed trading around earnings and M&A announcements in China's stock market. By adopting both indirect and direct informed trading measures, it is found that informed tradings are more pronounced before earnings announcements than before M&A announcements. We further investigate the relation between firm characteristics (size and profitability) and the level of informed tradings. Results show that smaller companies have more informed trading before both earnings announcements and M&A

announcements. Companies of both high and low profitability show more informed trading than companies of medium profitability before earnings announcements. Nevertheless, only companies with poor financial performances have higher levels of informed trading before M&A announcements. Moreover, companies with higher level of informed trading seem to have less or even negative long term benefits from M&As on both stock price and financial performance. We argue that this could reveal that the initial motivation of mangers to launch M&A transactions is the gains from insider tradings instead of the long term interests of the companies. We conjecture that informed tradings prior to M&A announcements by small and non-profitable firms could be executed by actual insiders as a result of agency problem and weak market regulation in China.

Acknowledgments

First of all, I would like to express my gratitude here to Dr. Tao Juan who guided me into the research with her patience. She encouraged me all the time and supported me a lot, and so that I could carry out this work. Under her supervision, she guided me in detail and suggested me real impressive way of working. I feel so lucky and grateful to be able to discuss and work with her. Secondly, I would like to thank my family, in particular my wife Xiaoting Dai. She is also my colleague in the University. I feel really lucky to have her. Her support and patience help me a lot in this journey. I would also like to thank my parents and my little lovely daughter. Their accompany means a lot to me. Thirdly, I would like to thank my thesis committee. I am grateful to have you for examining my thesis because it is a heavy task to go over 100 pages of anything. My thanks also go to many professors, doctors and fellow PhD students in my university, with whom I received impressive suggestions and shared useful information. Their support also helps me a lot.

Index

Introduction

1 Motivation and Research Questions....7
2 Data and Methodology.... 9
2.1 Data.... 9
2.1 Methodology....9
3 Main findings and Contributions....10

Chapter 1
Stock Market Intraday Patterns and Information Flow

Abstract 12
1 Introduction 13
2 Literature Review.... 14
3 Data and Descriptive Statistics 16
4 Methodologies and Empirical Results....16
4.1 Volume and Trades 16
4.2 Return and Volatility 18
4.3 Liquidity continuous 19
4.4 Levels of Informed Trading 22
4.5 Test of Intraday Momentum Effect....24
5 Robustness test 25
5.1 Price Discovery 25
5.2 Profit Seeking Test 27
6 Conclusion.... 29
References....30

Chapter 2
Research on Information Driven Trades in China

Abstract 33
1 Introduction 34
2 Literature Review 37
3 Data and Descriptive Statistics 39
4 Baseline VDPIN Model, Trade Size, and Composition 41
4.1 Baseline VDPIN Represented by Contrarian Trades 41
4.2 VDPIN Measure for Trades of Different Sizes 43
5 Large Trade Price Impact and VDPIN-P 47
5.1 Large Trade Price Impact 47
5.2 VDPIN Modification with Price Impact 49
6 Predictive Regression Analysis on the Information at Market Close 53
7 Robustness Tests 49
7.1 Autocorrelation Test 55
7.2 Information Advantage Test 56
8 Conclusion 60
References 62

Chapter 3
Informed Tradings Prior to Earnings and M&A Announcements in China Stock Market

Abstract 65
1 Introduction 66
2 Literature Review and Hypotheses 68
2.1 Background： Unique Situation in China Stock Market 68
2.2 Literature Review 70
2.2.1 Insider trading and informed trading 70
2.2.2 Insider trading measures 70
2.2.3 Insider trading and Earnings and M&A announcements 71
2.2.4 Insider trading and Corporate Governance 72

2.3 Hypotheses Development 73
3 Data 75
4 Methodology and Empirical Results 77
4.1 Indirect Evidences of Informed Trading around Announcements 77
4.1.1 Information Asymmetry Prior to Announcements 77
4.1.2 Cumulative Abnormal Returns around Announcements 80
4.1.3 Abnormal Turnover around Announcements 82
4.1.4 Trade Imbalance around Announcements 83
4.2 Predictability of Post-Announcement Abnormal return by Pre-Announcement Trading 85
4.3 Informed Trading Measured by PIN and VDPIN-PI around Announcements 87
4.3.1 Company Size and Informed Trading around Announcements 87
4.3.2 Financial Performance and Informed Trading Around Announcements 90
4.4 Relationship of Firm Characteristics and Informed Trading 93
5 Robustness Tests 94
5.1 Actual Insider Trading Event Study 94
5.2 Long Term Influences of M&As for Companies with Different Size Proftability and Levels of Informed Trading 95
6 Conclusion 97
References 98

Conclusion 101

Future Works 103

Appendix 104
List of Figures 104
List of Tables 105

Introduction

1 Motivation and Research Questions

China, the second largest economic entity in the world, is generally considered having less effective implementation of regulations on corporate disclosure and insider trading than developed markets. Furthermore, China's stock market participant composition differs in that there are more retail investors and fewer institutional investors. According to the statistics released by CSRC (China Securities Regulatory Commission) recently, more than 70% of trading volumes are contributed by retail investors in the past decade. With a higher level of information asymmetry, it is worth examining China's market to study information related micro-structure effects and trading behaviors, which may differ from that of other developed markets. By doing so, this study aims to provide insights for not only academic researchers, but also investors and regulators in China.

There is a common phenomenon that have been previously reported in many markets, that is, investors prefer to trade at the beginning and ending periods more than during other trading time within a day. We believe this is a suitable starting point to search for possible explanations for this phenomenon as well as its influences on some other trading related variables (e.g. return, volatility, liquidity and price discovery). Based on previous literature, investors prefer to trade in the first and last half hour because of higher returns or lower liquidity cost (Barclay and Warner, 1993). However, in a market dominated by retail investors with high trading volume and turnovers, liquidity should not be a concern. Higher abnormal returns might be the main motivation for rational investors to trade in the first and last half hour. We infer that U-shaped intraday patterns of trading volumes as well as other related variables should be mainly driven by similar patterns of profit-seeking trading actives such as informed tradings, given that preferential access to information or superior capabilities to process information are the main sources of abnormal returns. Previous literature (e.g. Madhavan et al., 1997; Barclay and Hendershott, 2003) provide both theoretical and empirical support to our hypothesis that informed trades concentrate at the opening, and sometimes the closing, period of the exchange. The first empirical chapter of this thesis seeks to find preliminary evidence for this hypothesis.

Another strand of research focuses on the order submission strategies of informed traders. Kyle (1985) suggests that profit-maximising informed investors may attempt to camouflage their information and reduce the price impact by spreading trades over time. Barclay and Warner (1993) find that informed traders will concentrate on medium-sized trades, given their concerns such as costs related to regulatory requirements, delays and brokerage commission. In contrast, Barardehi et al. (2018)

argue that aggressive market orders in large sizes may be used during high-liquidity times when the price impacts are small. This thesis attempts to examine the trading strategies of informed traders in China' s stock market, which is dominated by retail investors who are usually perceived to be irrational and impatient. To maximise their profits, do informed traders in China tend to behave cautiously and camouflage their trades or to trade aggressively, given the atmosphere of urgency and the likely consequence of high delay costs? The second empirical chapter of the thesis attempts to examine the trading strategies of informed traders in China' s stock market.

Based on the results of the first two empirical chapters, we conjecture that the informed trading activities should be more pronounced during significant company events that contain more information than during regular periods, which is also explained by weak regulation and associated costs in China's stock market. We extend our study to examine informed trading activities around significant company events. There are two types important firm announcements containing a great deal of information: the scheduled earnings announcements and the unscheduled merger and acquisition (M&A) announcements. Abundant evidence of informed tradings around earnings announcements are documented in the literature (Park et al., 2014; Le et al., 2019). Comparatively, less is reported regarding informed tradings around M&As announcements. Aktas (2007) conducts a similar study with ours. Since M&As are one of the most important company-specific events, the stock price movements after the M&A announcements are normally decided by rational market evaluations of the value created by the M&As. It might be true in developed markets. In China, however, it is unusually common that share prices of the acquiring companies will always increase dramatically following the M&A announcements regardless of whether the deal is beneficial or not. This creates opportunities to obtain huge abnormal gains for anyone who can have preferential access to insider information of the M&As. Exploring the reasons for this phenomenon, and more specifically, identify important firm characteristics that are closely associated with this phenomenon, would provide insights for investors, companies and also regulators to better understand the phenomenon. The third empirical chapter of this thesis aims to find evidence for the existence of informed trading around significant company events, as well as explore possible company characteristics that may explain different levels of informed trading around the events.

The thesis is consist of an overall introduction to the thesis, three empirical chapters (Chapters 1, 2 and 3) as the main body and a conclusion at the end.

2 Data and Methodology

2.1 Data

The data applied in this thesis is the quote and trade data from China's market. The whole dataset consists of two parts. The first part of our sample data consists of 300 constituent stocks of the CSI300 index from January 2012 to December 2014. CSI300 stocks are from both the Shanghai and Shenzhen Stock Exchanges, and cover about 60% of China's overall stock market capitalization. To test hypotheses about informed tradings around company announcements, we also collect the second part of the data consisting 100 stocks ranked as the last 100 by firm size in CSI Smallcap 500 index from October 2013 to September 2014. During this period, there are 1000 earnings announcements of 300 stocks and 210 M&A announcements of 161 stocks in total by the included companies. Detailed information and descriptive statistics of our data can be seen in the relevant empirical chapters.

2.2 Methodology

To verify the first hypothesis of this study (the main reason for preference to trade in the first and last half hour of a day by Chinese investors is to seek higher return rather than lower liquidity cost), six liquidity measures including absolute spread, effective spread, relative spread, depth, Rupee depth and Amihud ratio are used to measure liquidity. Since abnormal return lies in undigested incoming information, we try to test the intraday information flow by examining the probability of informed trading across a day. We apply two different informed trading measures, which are PIN measure introduced by Easley et al. (1993) and the contrarian trades of Avramov (2006). Furthermore, as literature suggests, informed trading helps improve price discovery (Nowak et al., 2011). We also study whether active trading in the beginning and ending period of a day may contribute more to price discovery. For this purpose, we employ the WPC (Weighted Price Contribution) approach which is first proposed by Barclay (2003) to test the intraday pattern of price discovery. Moreover, the market intraday momentum effect is another approach of detecting intraday information flow. We then apply the method of Gao et al. (2018) to find additional evidence that may provide support to our first research hypothesis.

In the second empirical chapter, which is to examine the intraday pattern of information driven trades and informed traders' order size strategies in China's stock market, we first use contrarian trades to represent informed trades, noted as the baseline volume-based dynamic probability of informed trading (baseline VDPIN) by Avramov et al. (2006). To further examine the trade-off between delay cost and camouflage, we then employ the baseline VDPIN for each trade category of small, medium, and large sizes. The results help us identify the non-negligible price impact (PI) of large trades, based on which we propose a modified model, VDPIN-PI, which better captures the trades with information advantage than the baseline model. Moreover, autocorrelation test and information advantage test are applied to ensure the robustness of our main results obtained from applying the modified model.

In the third empirical chapter of studying informed tradings around earnings and M&A announcements in China's stock market, we first adopt indirect informed trading measures including cumulative abnormal returns, abnormal turnover and trade imbalances (Park et al., 2014; Le et al., 2019). Predictability of post-announcement abnormal returns by pre-announcement tradings is then perfromed to investigate efficacy of these indirect evidences. To verify our hypotheses, direct measures of informed tradings including the unconditional probability of information-based trading (PIN) by Easley et al. (1996) and the Volume Weighted Dynamic Probability of Informed Trading of Price Impact (VDPIN-PI) developed in Chapter 2 are also applied. Finally, we employ the OLS regression proposed by Aslan (2011) to investigate the relationship between firm characteristics (firms size, profitability) and the level of informed trading. Actual Insider Trading Event Study and Long Term Influences of M&As for Companies are employed as robustness tests.

3 Main findings and Contributions

The conventional wisdom to explain the U-shaped intraday trading pattern is low liquidity cost during the opening and ending periods of a day, which might be true in developed markets such as the U.S. market. We suspect that we cannot simply borrow others' explanations to understand China's market, which is dominated by a large number of retail investors, who generate high trading volume and frequent turnovers and provide sufficient liquidity throughout the trading time. Therefore, liquidity should not be a major concern by traders in China. Our assumption is that the abnormal returns associated with unbalanced intraday information flow should be the main incentive for investors to trade most heavily in the first and last half hour of a day in China's stock market. By examining the liquidity patterns over a day, we find no evidence of lower liquidity cost in the first and last half hour of a trading day. On the contrary, U-shaped intraday patterns of both informed trading and price discovery are identified. Moreover, a clear intraday momentum effect is also observed. These results provide strong supports to our conjecture. Therefore, we contribute to the literature by providing alternative explanations for the widely observed intraday U-shaped trading patterns based on more thorough understanding of China's market participants and market structure.

Our second contribution lies in that we sought for more complete and insightful explanations for the intraday informed trading pattern beyond that explained by the time-of-day effect. First, by carefully performing informed trading composition analysis, we identify intraday variations in the composition of small, medium, and large trades, which reveals the implemention of different order size strategies during different time periods by informed traders. Second, we investigate information predictability from early morning to market close and from late afternoon to the next day, which point to intraday momentum in informed trading pattern.

Our third contribution is in terms of modeling. It is straightford to understand that large trades have price impact, which explains why informed traders may prefer to trade in medium size-orders even it may involve delay costs. However, in the various informed trading measures identified from the literature, little is done to accommodate large trade price impact. To address this problem, we explicitly incorporate the non-negligible price impact (PI) of large trades into informed trading measure and propose a modified informed trading model, the VDPIN-PI, which is found to be able to better capture the trades with information advantage than that by the baseline model.

Finally, we conjecture that informed trading is more often carried out on small firms' shares, because small firms often have less information disclosed and less analyst following than large firms. Also, we suspect that managers of poor financial performance firms are under pressure from shareholders and investors and have more incentive to initiate some sort of deals such as M&As that can help boost their stock price, at least in the short term. To investigate these hypotheses, we comparatively examine informed trades around scheduled earnings announcements and unscheduled M&A announcements in China's stock market for firms of two main different characteristics, that is, firm size and profitability. We document that smaller companies indeed have more informed tradings before both earnings announcements and M&A announcements. It is also found that companies with poor financial performance have higher levels of informed trading before M&A announcements. Moreover, companies with higher level of informed tradings seem to have less or even negative long term benefits from M&As in terms of both stock price and financial performance. Therefore, our fourth contribution is that by comparatively examining informed trades around two types of corporate events for firms of different sizes and profitability, it reveals a series of driving factors of informed trades, such as insider information, weak external monitoring and regulation, and agency problem.

Chapter 1

Stock Market Intraday Patterns and Information Flow

Abstract

There is a common phenomenon that investors prefer to trade in the first and last half hour more than other trading time within a day in almost all stock markets. This study focuses on two main research questions related to this phenomenon: the influences of it on market fundamentals (return, volatility, liquidity and price discovery) and also possible explanations for this phenomenon. Using high-frequency quote and trade data of all stocks from CSI300 index, we find that the all market foundations especially liquidity show clear similar patterns as trading volume does. This suggests that investors' preference on trading timing over day could have a positive influence on market fundamentals. Furthermore, the probability of informed trading (PIN) and price discovery (Weighted price contribution, WPC) are also found to be higher at the beginning and ending period of the day. A clear intraday momentum effect is also observed. Based on the overall results, we conjecture that the information flow across day could be a reasonable explanation for this phenomenon.

1 Introduction

Intraday trading volume displays a U-shape pattern in almost every stock market. In China, we also find evidence that investors prefer to trade in the first and last half hour more than other trading time within a day. Explanations for this phenomenon, however, are not concluded. This research seeks to identify traders' incentives that cause the intraday trading volume pattern as well as the influences of it based on market fundamentals (return, volatility, liquidity and price discovery). We use tick-by-tick trading data of all stocks from CSI300 index in this study, and the total sample period is from Jan 2012 to July 2014.

We conjecture that investors prefer to trade in the first and last half hour because higher returns could be earned during those periods, which may be caused by lower liquidity cost when trading is more active. Hence, we investigate the intraday pattern of liquidity and returns. Six liquidity measures including absolute spread, effective spread, relative spread, depth, Rupee depth and Amihud ratio are used in testing liquidity cost. However, for all liquidity measures, the results do not suggest lower liquidity cost in the first and last half hour of a trading day. Therefore, investors in China are motivated to trade more actively in the beginning and ending period of a day to earn higher risk-adjusted return which is not explained by liquidity cost. In this case, our explanation for this is that liquidity cost is minor compared to other factors in affecting returns in China.

The underlying assumption of this work is that information should be the essential incentive for investors to trade. Since more information should attract more informed trading, we test the probability of informed trading across day applying two different approaches, which are PIN measure from Easley et al. (1993) and the contrarian trade of Avramov (2006). Both results showed there are indeed more informed trading at the beginning and ending period over a day. Furthermore, as literature suggests, informed trading helps improve price discovery (Nowak et al., 2011). We also studied whether active trading in the beginning and ending period of a day may contribute more to price discovery. For this purpose, we employ the WPC (Weighted Price Contribution) approach which is first proposed by Barclay (2003) to test the intraday pattern of price discovery. The results show that price discovery is indeed higher in the first and last half hour of a day compared to other trading time. Barclay (2003) suggests that the first half hour is the digestion of information from last non-trading period and last half could refer to the expectations for future information. In order to improve the reliability of this underlying argument, we than test of Intraday Momentum effect in Section 4.5. Following the work of Gao et al. (2018) and Chu et al. (2019), we find clear evidence that the first half hour return could predict the last half hour return. This could be another strong evidence supporting that the U-sharped pattern can be explained by intraday information flow.

2 Literature Review

The debate of the efficiency of financial markets has led to volumes of research, however, consensus has not been reached. Fama (1970) defines the efficient-market hypothesis (EMH), in which explains a market with all relevant information is quickly and correctly reflected in its prices. Nevertheless, critics of the EMH believe that information asymmetry, irrational behavior of investors and persistent market anomalies (Lim and Brooks, 2011). The dynamic of financial markets is complex because of information, a random diversification of investment horizons of participants, and multiple feedback mechanisms (Zhang et al., 2022). The dynamic of data is strongly correlated with information flow and market efficiency. Some of the stylized facts can be found in Kaldor (1961), Goodhart (1990), Guillaume et al. (1997), Cont (2001), and so on. The low-frequency and high-frequency data both allow researchers to conduct a set of stylized statistical facts research in the literature. As Nowak et al. (2011) documents that the price discovery and volatility dynamics analysis of financial markets require intraday data as the immediate reaction of markets to new information can be discovered only at high frequencies.

Some classical intraday characteristics for financial markets are revealed from empirical research. For example, Admati and Pfeleidere (1998), and Brock and Kleidon (1992) point out the calendar effect and intraday U pattern with explanations. Intraday volatility and volume with U pattern are also found in some mature markets (Andersen and Bollerslev, 1997; Hasbrouck, 1999; Andersen et al., 2001). Significant positive correlation between volatility and volume, which demonstrates the activity of the trades, and the asymmetric distribution of intraday trades, which probably contribute to the intra-day effect are found in their research. Ding and Lau, (2001) use intraday trading data of some stocks to demonstrate the U-shaped pattern, and found that volume, trading spreads, and trading frequency also follow this pattern. Andersen (2000) prove the existence of long-memory interdaily volatility dependencies from high-frequency returns. The price volatility was high around the opening hours in the morning and closing hours in the afternoon; other variables, such as transaction frequency, volume and trading spread also appeared to be moving in the U-shaped (Mcinish and Wood,1990, 1991,1992). Qu and Wu (2002) study the intraday pattern of volume in the Chinese stock market and derived a conclusion similar to that of foreign researchers, i.e., the intraday volumes moved in an inverted U pattern. However, the spread moved in an L-shaped path, unlike the U-shaped of intraday movements in mature markets like the NYSE. Fang and Wang (2004) analyze the U-shaped characteristics of the Shanghai stock market, and established FFF models to estimate the intraday return patterns. Wei and Ma (2007) use high frequency data of fund index in Shenzhen Exchange Market to analyze the intraday periodicity. The qualitative analysis of high frequency return indicates that the fund market has the similar periodicity with the stock market. Liu et al. (2008) empirically analyze patterns of intraday movements of price and volume in Shanghai and Shenzhen A-share stock markets, using transaction data of five minutes periods. Gao et al. (2018) show an intraday momentum pattern in the high-frequency data from S&P exchange-traded fund, especially on high-volatility, high-trading-volume days, recession days and the days of releasing major macroeconomics news.

Several other explanations also have been offered in the literature for such a concurrent high volume and wide spreads. Brock and Kleidon (1992) predict that market liquidity will be inelastic at both the open and the end of a trading day with an NYSE specialist market maker with monopoly power. This indicates that traders are simply adjusting their portfolios to achieve an optimal portfolio mix or transfer overnight risk. However, this is not tenable in an order driven market, because there is no designated market maker. In addition, it is difficult to find a model that can explain such concurrent behavior. Admati and Pfleiderer (1988) observe that high trading volumes occur at arbitrary trading times because high volume periods attract both informed and discretionary traders. They also find that it is the optimizing behavior of these two players that results in the U-shaped of both volume and spread related measures. Fan and Lai (2006) test this proposition while examining the intraday variations in trading volume and bid-ask spread on the Taiwanese stock exchange (an order driven market) with mixed results mixed. They also find that the reason for the beginning of the intraday pattern was related to the model proposed by Admati and Pfleiderer (1998), but the reason for the end of the intraday pattern was due to the model by Brock and Kleidon (1992). Nevertheless, for the China stock market, such a U-shaped may be simply explained by volume traders dominating despite wide spreads with the reason that returns are the highest when volume is the highest.

A lot literature investigats intraday volatility in different financial markets. For example, Nguyen and Phengpis (2009), Ozenbas et al. (2010), Tissaoui (2012), Belhaj, et al. (2015) and Inci et al. (2021) observe a U-shaped intraday volatility curve. They indicate that heightened volatility when the market opens in the morning and before the close of the market for the day, with stability and relative lower volatility throughout the middle of the trading period. Zhang et al. (2022) propose a methodology that consider both intraday patterns and interday dynamics of the stock market. They find that the variance of intraday returns and the Amihud illiquidity in the post-Crisis period are both greater than values in the pre-Crisis period. Thus, the majority of scholars mentioned above focus their works on volatility of transaction variables of securities markets, fund market and exchange market. There is little discussion which introduced in futures market.

3 Data and Descriptive Statistics

This study is based on quote and trade data from China's market. Compared with developed markets, China's stock market is believed to have less effective implementation of regulations on corporate disclosure and insider trading. Further, China's stock market participant composition differs in that there are more retail investors and fewer institutional investors. With a higher expected level of information asymmetry, it is worth examining China's market to study informed trading behavior, which may differ from that of other developed markets. The sample data is obtained from the Wind database[1], consisting of 300 constituent stocks of the CSI300 index. CSI300 stocks are from both the Shanghai and Shenzhen Stock Exchanges, and cover about 60% of China's overall stock market capitalization. Our sample includes data from January 2012 to December 2014, and buyer- and seller-initiated trades are indicated for each trade. The Shanghai and Shenzhen Stock Exchanges both employ the call auction trading mechanism from 9:15 to 9:30 am to open the market and Shenzhen Stock Exchange also employs this mechanism from 14:57 to 15:00 pm to close the market. We exclude all call auction periods of the two exchanges from our sample because quote and trade data are not available. Finally, our dataset includes all transactions of the 300 stocks during the continuous auction periods of 9:30 to 11:30 in the morning and 13:00 to 15:00 (13:00 to 14:57 for Shenzhen Stock Exchange) in the afternoon during the three years. Within the sample period of 729 business days, there are 1.2215 billion trades in total, including 643.48 million (52.65%) buyer-initiated (buy) trades and 578.71 million (47.35%) seller-initiated (sell) trades.

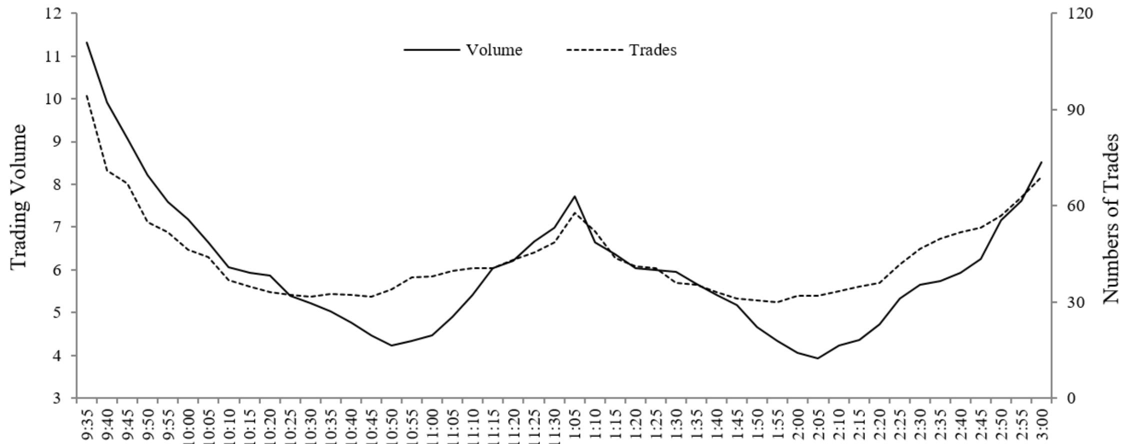
4 Methodologies and Empirical Results

4.1 Volume and Trades

Following the work of Ekman (1992), we first calculate the volumes and numbers of trades to explore the intraday patterns of them. Results can be seen in the following figure where both of them show clear U-shaped intraday pattern.

[1] Website of Wind Database: www.wind.com.cn

Figure 1: **Intraday Patterns of Volume and Trades**



Note: The scale for average trading volume is displayed on the left Y-axis in the unit of "round block", which represents 100 shares. The scale for average numbers of trade is displayed on the right Y-axis. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day.

There is clear a U-shaped pattern of trading volume and numbers of trades which show investors prefer to trade in the first and last half-hour. Trading is high at the morning opening, then goes down gradually, and finally reaches a stationary situation after about 30 minutes. worthy of mention is the fact that the volume also has a rise at the closing time, but not the same big as the opening time. Moreover, during the lunch break ($11:30$ to $13:00$), the trading volume has a slight but significant increase, similar to a new morning opening. The movement of volume correlates strongly to the trading mechanism.

Since there is great shadow marginal trading in China stock market.[2] Because of the limited ability to endure risks, there is often great pressure on investors because of the high volatility around the opening hour. Investors with more information tend to trade following with information, so the volume at the early opening is large. The larger the volume is, the more is the information that the ordinary investors can detect from the behavior of institutional investors, and the larger is the possibility that they would adjust their positions, and the higher would be the price volatility. After about 30–40 minutes from the morning opening, information will be fully absorbed, and prices and volumes will stabilize. The high volatility of volume around the opening hours comes from the release of overnight information, which is similar to the results of Easley D and O'Hara M(1992),volume would go up irrespective of whether the information of the market is positive or negative. Similarly, information also accumulates between the lunch break, though there is no call auction during these

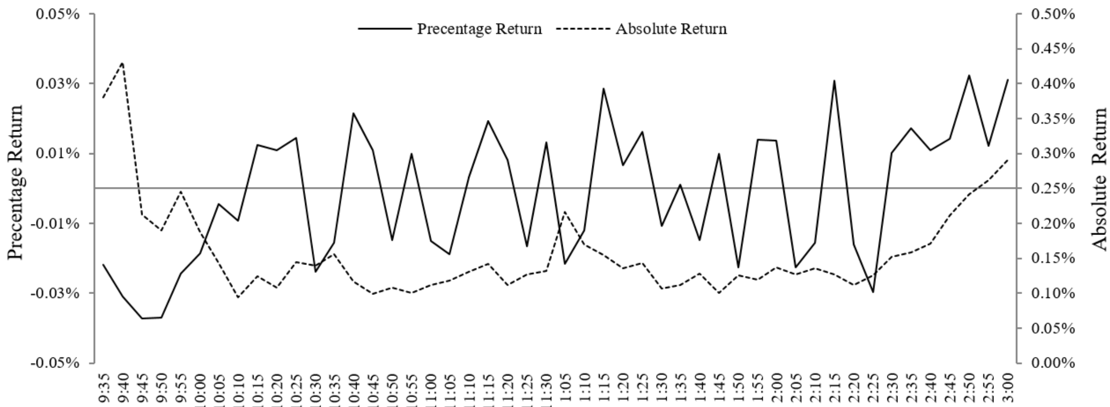
[2]Great amount of capital entered the service which should be only provided by dealers in developed of offering leverage funds during 2014 and 2015. This significantly increases the risks of leveraged retailed investors and encourages them to trade more frequently. The bull period from 2014 to 2015 is called leverage driven bull. And the deleverage action of the regulators are believed to responsible for the following market crash.

periods. We believe that release of information after the rests would increase price volatility and especially volume, which increases significantly around the reopening of the market after the lunch breaks. The volume increases significantly but not as much as in case of the morning openings since breaks are not long,.

4.2 Return and Volatility

Following Admati and Pfleiderer (1988), we observe the percentage return and absolute return since return itself can be seen as the most basic measure of volatility.

Figure 2: **Intraday Patterns of Return and Volatility**



Note: The scale for average percentage return is displayed on the left Y-axis. The scale for average absolute return is displayed on the right Y-axis. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day.All the results are firstly average across stocks than across time.

As can be seen from Figure 2, the percentage return does not show any pattern during the day since return itself seems to be random between positive and negative results. Only the first 15-minutes from 9:15 to 9:30 seem to be negative continuously. This could be because that there is an action period before active trading which starts at 9:30. This 15-minutes mainly focuses on digesting overnight information. And investor could have asymmetric reflections for good and bad news. As a result of loss aversion, it is more likely to form a unified pricing opinion on bad news. Furthermore, we can obverse a clear U-shaped pattern of absolute return during the day which is also similar to the pattern of trading numbers and volume. The highest absolute return is at the first half hour from 9:30 to 10:00am. The ending half hour as well as the lunch break also shows higher absolute return than usual time. The result of absolute return may suggest that investors do have higher chance to gain more profit in the first and last half hour of the day. However, despite of risk, return should not be the only propose of rational investors. We cannot simplify judge that investors choose to trade in these period just seeking higher profitability.

4.3 Liquidity continuous

Another possible expatiation is that traders intend to trade when market liquidity is high. The measurement of market liquidity involves tricky issues that may be attributed to the following factors. First is the realization that there is no single all-encompassing measure of market liquidity. The measures by construction are multidimensional because a liquid market allows trading of any volume size and demands of an immediate execution of such trading with no price impacts. Secondly, market efficiency requires continuous and significant price adjustments to market news. Thus, any empirical study should select proxies that meet these two competing requirements. Another issue relating to liquidity measurement is that the market system and trading mechanism also play roles in deciding a valid proxy for liquidity. The trading environment can be significantly different between dealer market and pure limit order market. Moreover, institutional changes, rules of a stock market operates, changes in the government policy and structural changes in the domestic or external economy may all affect the liquidity measures, in which at least some of them are inconsistent over time. Due to these reasons, there is no single agreed upon proxy for measuring liquidity. As per Aitken and Forde (2003), there are 68 extant measures of liquidity in the market used for various purposes. These measures or proxies differ depending on the frequency of data that we use, in which is based on intraday, daily, monthly or annual data. While not all extant measures can be used to measure the liquidity of any given market type or for any given frequency of data. In practice, these measures are used interchangeably, irrespective of the type of market or frequency of data. Liquidity proxies also differ depending on whether we want to comment on the liquidity of an entire market or individual stocks, or even compare across stock exchanges within a country and across countries. Therefore, four most commonly used liquidity measures are applied to test the market liquidity including effective spared, market depth, Amihud ratio and flow ratio. All the results are firstly average across stocks than across time.

Effective spread

Spread is the most common measure to work on the depth of a market. The bid-ask spread is a common liquidity proxy (see Amihud & Mendelson, 1986). The difference between the ask-price and the bid- price and its related measures gives an approximate cost to be incurred when trading. However, the principal determinants of bid-ask spread are fixed costs, adverse selection costs, and inventory costs. While the seminal article by Kyle (1985) focuses on the adverse selection component, Glosten and Milgrom (1985) capture the notion of asymmetric information. To consider market liquid, the spread measures should have low values. We also use effective spread, since it cancels out the price difference of each stock.

$$Effective\ Spread = \frac{|\ p_{i,j} - p^M_{i,j}\ |}{p^M_{i,j}} \tag{1}$$

where $P_{i,j}$ is the price for stock i during interval j, and $P^M_{i,j}$ is mid-quote for stock i during interval j.

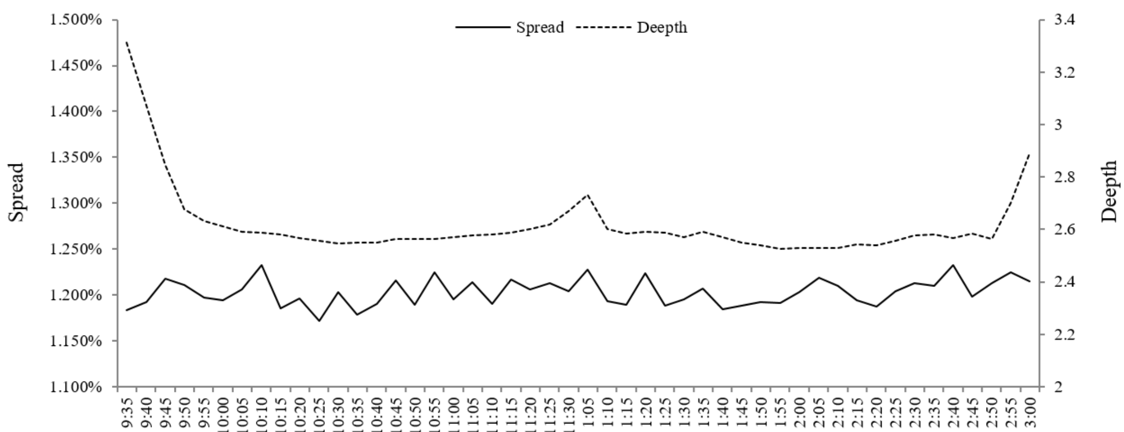
Depth

Depth is one of the traditional measures of liquidity, relates to the quantity that can be traded in a market and is closely related to spread. For example, Corwin (1999) uses this measure to test the market depth that differs significantly among the specialist firms, and suggests different execution costs and liquidity among NYSE specialist firms. Greene and Smart (1999) examine whether depth increases due to noise trading. This can be calculated in the following way,

$$Deepth = log(q^A_{i,j}) + log(q^B_{i,j}) \tag{2}$$

where $q^A_{i,j}$ is volume of waiting asking orders for stock i during interval j, and $q^B_{i,j}$ is volume of waiting bidding orders for stock i during interval j.

Figure 3: **Intraday Patterns of Spread and Depth**



Note: The scale for average effective spread is displayed on the left Y-axis. The scale for average market depth is displayed on the right Y-axis. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day.

As can be seen from Figure 3, the effective spread does not show any pattern during the day. This could be because our data set is constant of the 300 largest stocks in China. And the trading frequency in China is also much higher than other developed markets. With plenty of liquidity supply, the spreads have been kept at the minimum tick size of 0.01 RMB for CSI 300 stocks in most time. Meanwhile, a clear U-shaped pattern of market can be observed during the day. The highest market depth is still at the first half hour from 9:30 to 10:00am. The ending half hour as well as the lunch break also show higher market depth than usual time. This means there are more orders waiting at the order book, although the spread does not change during the day. Therefore, the market could absorb more active orders at one tick price. We can conjecture that the market does show higher liquidity in the firsts and last half hour of day.

Amihud Ratio

If the stock price moves significantly in response to little volumes, the stock has a high value of Amihud measure and implies that the stock is illiquid. Amihud (2002) shows that over time expected market illiquidity positively affects ex ante stock excess return, suggesting that expected stock return partly represents an illiquidity premium. While this is a very popular measure, it could be affected by extreme values. Thus, the illiquidity ratio is a better proxy. Hasbrouck (2009) finds that these two measures are positively correlated with effective cost or spread by using daily data in cross section studies. Such a result helps us understand the relation between liquidity and transaction cost.

$$Amihud\ illiquidity\ Ratio = \frac{|r_{i,j}|}{V_{i,j}} \tag{3}$$

where $|r_{i,j}|$ is the absolute value of return for stock i during interval j, and $V_{i,j}$ is the accumulated trading volume for stock i during interval j.

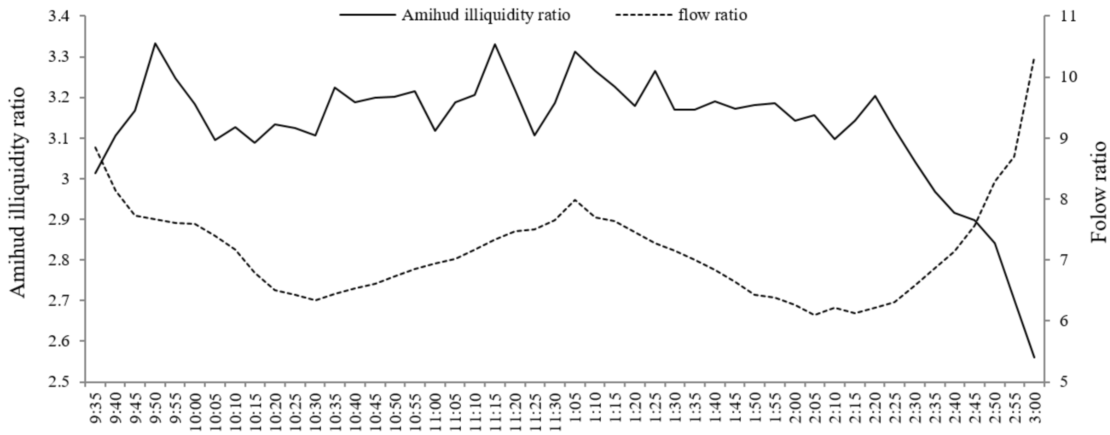
Flow ratio

As is recommended by Ranaldo (2001), the flow ratio is as follow:

$$FR = \frac{V_{i,j}}{WT_{i,j}} \tag{4}$$

where V_t is the average volume of return for stock i during interval j, and $WT_{i,j}$ is the average waiting time for stock i during interval j. Since flow ratio is the ratio of turnover to waiting time, it connects quantity and time dimensions of liquidity, with a high value indicating high liquidity

Figure 4: **Intraday Patterns of Amihud illiquidity Ratio and Flow Ratio**



Note: The scale for average Amihud illqiudity ratio is displayed on the left Y-axis. The scale for average flow ratio displayed on the right Y-axis. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day.

As can be seen from Figure 4, both measures have the expected shapes. The Amihud illiquidity ratio shows a reversed U-sharped pattern which means the same amount of trading volume would cause less price changes or price impact at the beginning and ending periods of the day. Furthermore, the flow ration shows ordinary U-shaped pattern. Both measure suggest there higher liquidity could be an incentive for investors to trade in the first and last half hour.

4.4 Levels of Informed Trading

To further test whether the intraday patterns are basically information driven, the most reasonable way is directly to test if there are more informed tradings during the opening and closing period. We implemented two commonly used methodologies in identifying the level of informed tradings as follow.

The Unconditional probability of information-based trading

The unconditional probability of information-based trading (PIN) is the most generally accepted method of detecting informed trading which is firstly proposed by Easley et al. in 1996. We apply this well-known methodology as the first way to test our hypotheses. In order to obtain this proxy of the presence of informed trades, the model parameters $\Theta = \{\alpha, \delta, \varepsilon, \mu\}$ are estimated by the maximization of a likelihood function. The likelihood of observing B buys and S sells for a trading interval is:

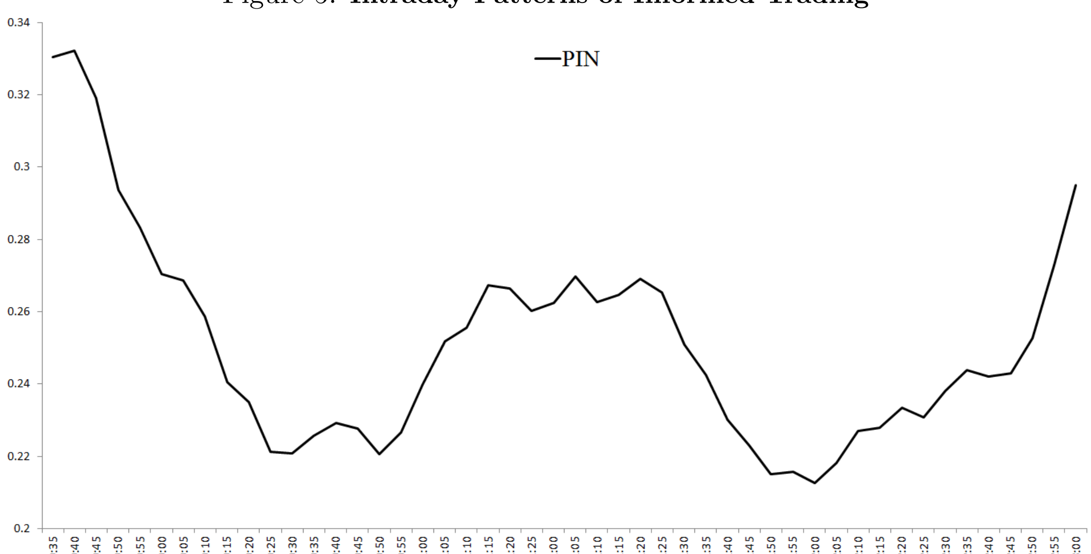
$$L(B,S \mid \Theta) = (1-\alpha) exp(-\varepsilon T)\frac{(\varepsilon T)^B}{B!} exp(-\varepsilon T)\frac{(\varepsilon T)^S}{S!}$$
$$+ \alpha\delta exp(-\varepsilon T)\frac{(\varepsilon T)^B}{B!} exp\left[-(\mu+\varepsilon)T\right]\frac{\left[(\mu+\varepsilon)\right]^S}{S!} \tag{5}$$
$$+ \alpha(1-\delta) exp\left[-(\mu+\varepsilon)T\right]\frac{\left[(\mu+\varepsilon)\right]^B}{B!} exp(-\varepsilon T)\frac{(\varepsilon T)^S}{S!}$$

where T corresponds to the total time (in minutes) of a single trading day. Since days are independent across the I trading days, the likelihood to maximize the following equation, with respect to the parameter vector Θ, yields maximum likelihood estimates of the parameters of interest. Starting from the number of buys and sells, the approach developed by Easley and O'Hara (1992) allows inferences of the presence of information-based trading on the market to be made. Easley et al. (1997) show that a 60- day trading window is sufficient to allow reasonably precise estimation of the parameters. However, to take advantage of the high frequency data, we introduced 90 intervals of 15mins for 5 trading day as one testing period for the following function:

$$L(M \mid \Theta) = \prod_{i=1}^{I} L(B_i, S_i \mid \Theta) \tag{6}$$

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{7}$$

Figure 5: **Intraday Patterns of Informed Trading**



Note: The level of informed trading measured by PIN is displayed on the Y-axis. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day.

As can be seen from Figure 5, the level of informed trading measured by PIN shows similar U-shaped intraday pattern with volume, volatility and liquidity. The highest level of informed trading appears during the first half hour from 9:30 to 10:00am. The ending half hour as well as the lunch break also show higher level of information than usual time. This suggests that the U-shaped pattern of return, volume, liquidity could be a result of investors trading on intraday or overnight information.

Volume-weighted Dynamic Probability of Information-based trading (VD-PIN)

However, some claim that the PIN has its limitations which may influence reliability of its results. Duarte (2007) find the PIN model cannot match the variability of noise trade in the data, and as a result these models are no more useful in identifying private information arrival when the price impact is not obvious. Moreover, the PIN relies on a set of data and produces on outcome for a period of time. It is not able to judge whether a single trade is informed or uninformed. Therefore, we also implied the *Volume-weighted Dynamic Probability of Information-based trading* which is firstly proposed by Avramov (2006) and adjusted by Chang (2014). The methodology allows to justify for each trade on whether it is informed or uninformed. Similar supportive results are achieved. We believe this methodology could provide us a reasonable way to discover informed trading in high-frequency world. Therefore, we modify and test it in Chapter 2 and Chapter 3. Details can be seen in Chapter 2,section 10.

In the previous sections, we show the intraday patterns of volatility, liquidity and of probability of informed trading. As discussed in results as well as past literature, we suggest that intraday or overnight information flow could be an possible explanation.

4.5 Test of Intraday Momentum Effect

Intraday momentum is explained as the first half-hour return on the market as measured from the previous day's market close predicts the last half-hour return. The intraday momentum is consistent not only with Bogousslavsky's (2016) model of infrequent portfolio rebalancing but also with a model of late-informed trading near the market close. It is another way of preforming the intraday information flow. Following the work of Gao et al. (2018) and Chu et al. (2019), we employ the simple predictive regression of the last half-hour return on the first half-hour return as follow:

$$r_{8,t} = \alpha + \beta_1 r_{1,t} + \beta_2 r_{7,t} + \beta_3 r_{n,t} + \beta_4 D_1 + \beta_5 D_5 + \epsilon_t$$

where $r_{8,t}$, $r_{1,t}$ and $r_{7,t}$ are the first, seventh and last half-hour returns on day t. $r_{n,t}$ is the overnight returns used to capture the arrival of news overnight (Wang et al., 2015) and information surprises (Polk et al., 2018), defined as percentage change of the opening price on day t relative to the closing price on previous day. Furthermore, since the day-of-week patterns have been investigated extensively in different studies.We include two dummy variables, $D_1$and D_2, in avoiding the day of the week effect to affect intraday returns patterns. $D_1 = 1$ if it is Monday, otherwise 0. $D_5 = 1$ if it is Friday, otherwise 0

Table 1:Regression Results of Intraday Momentum Test

	α	β_1	β_2	β_3	β_4	β_5
$r_{8,t}$	0.000865	0.129	-0.157	-0.0453	-0.0318	0.0702
	(3.870)***	(4.355)***	(-5.214)***	(-0.137)	(-0.0058)	(0.0079)

This table shows the regression results of Intraday Momentum Test. Newey and West (1987) robust t-statistics are in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

As can be seen in Table 1, we observe clear intraday momentum effect while the coefficient of β_1 positive and significant at 1%. According to the explanation of Gao et al. (2018), this could be considered as another strong evidence supporting that the U-sharped pattern are related to intraday information flow. Moreover, we also observe intraday reversal effect while the coefficient of β_2 negative and also significant at 1%. Chu et al. (2019) argue that intraday reversal challenges the efficient market hypothesis and indicates the China's stock market tend to be less developed as we acknowledge. There is no sign for the Day of the week effect.

5 Robustness test

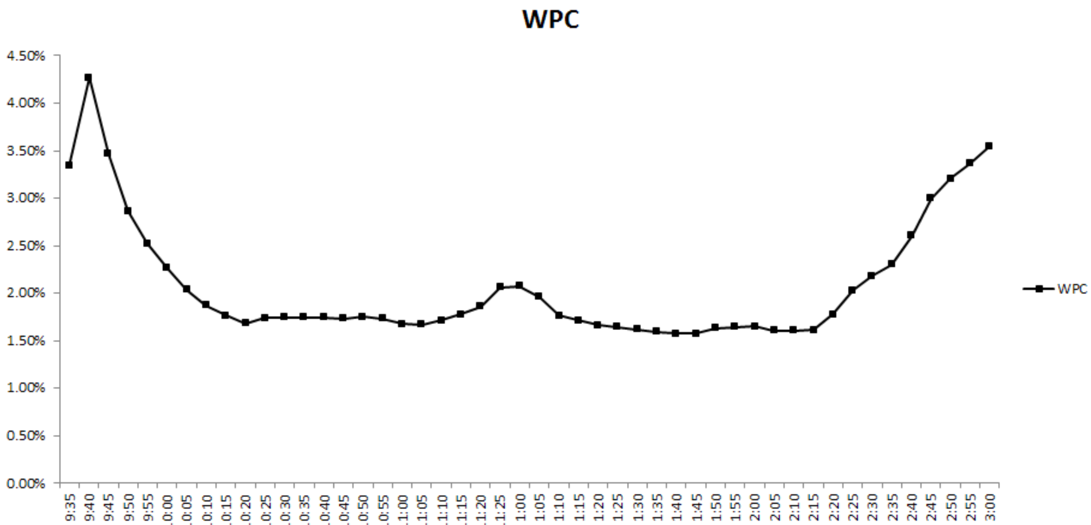
5.1 Price Discovery

Higher level of informed trading should increase the seeped of information digesting. And is would reflect in higher level of price discovery. Therefore, we extends to determine their relationships to the timing and amount of price discovery. We test the robustness of PIN and VDPIN as proxies of informed trading by examining their relations with the price discovery contribution. We adopt the WPC (weighted price contribution) approach used by Barclay and Warner (1993), Barclay (2003) and Cao (2000) to examine the price discovery pattern. For each day and each time interval j, the WPC is defined as:

$$WPC_{i,j} = \sum_{i=1}^{S} \left(\frac{\mid ret_i \mid}{\sum_{i=1}^{S} \mid ret_i \mid} \right) \times \left(\frac{ret_{i,j}}{ret_i} \right) \tag{8}$$

where $ret_{i,j}$ is the logarithmic return for stock i during interval j and ret_i is the open-to-close return for stock i. The first term of WPC is the weighting factor across stocks. The second term is the relative contribution of the return during period i to the total return on that day. Aggregating $WPC_{i,j}$ across the 300 stocks over the sample period, the intraday pattern of weighted price contribution is reported in the following Figure . The WPC shows similar intraday patterns.

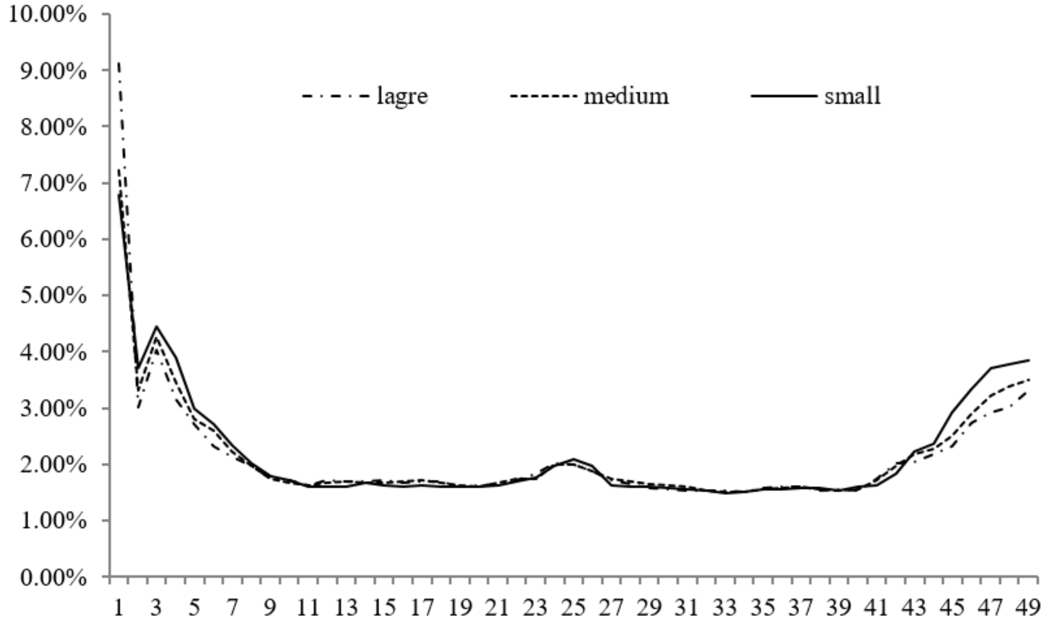
Figure 6: **Intraday patterns of Price Discovery**



Note: The weighted price contribution is displayed on the Y-axis. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day.

Figure 5 shows that the intraday WPC pattern is mostly as the same as the trading volume pattern. And also shows no significant difference over time in our data period. The only point should care is that the first five minutes' WPC is not the highest over day while the trading volume does. This can be explained by the 15 minutes aggregate auction process before formal trading which starts at 9:30AM every day. Therefore, we also complete the test by considering the aggregate auction and divide the sample by different market values. (Large: over 10 billion, medium: 5-10billion, small: below 5 billion). Results are as follow:

Figure 7: **Intraday patterns of Price Discovery including aggregate auction period for large medium and small companies**



Note: The weighted price contribution is displayed on the Y-axis. The numbers of interval displayed on the X-axis denotes each five-minute interval within the day expect the first interval represents the action period from 9:15 to 9:30 of each day.

We can see that the aggregate auction process does have strong price explanatory power. And the aggregate auction process has higher WPC for large firms other than small firms. However, in regular trading time, small firms have a deeper U-shaped WPC pattern than large firms. And the detailed numbers can be seen as follow.

5.2 Profit Seeking Test

Informed traders seek profit and they should be able to gain high returns because of information asymmetry. We design a way to test whether these possible informed trades are able to gain their profits. The results from both WPC test and VDPIN test suggest that the 30 minutes may contain more informed traders. The trades in these periods have stronger predictability for 30 minutes future returns. Similar works can also be seen from Gao (2018). The methodology is as follow:

$$Acc = \frac{NB_t}{NA_t}(P_t{<}P_{t+1}) + \frac{NS_t}{NA_t}(P_t > P_{t+1}) \tag{9}$$

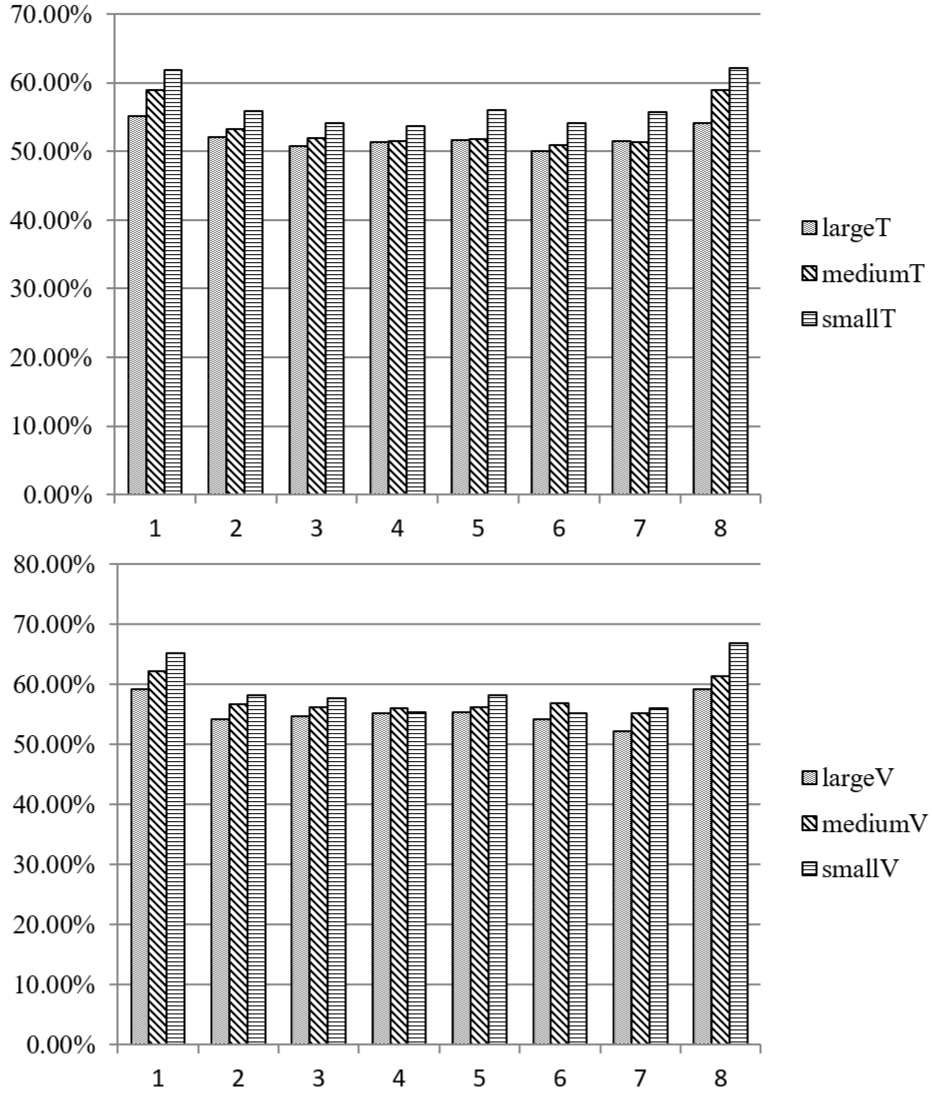
where $P_t$is the transaction price at time t and $P_{(t+1)}$ is the price 30 minutes later. NB is the numbers that all the trades which are able to buy at lower prices than 30 minutes later. NS_t is the numbers that all the trades which are able to sell at higher prices than 30 minutes later. NA_t is the total numbers all trade. Acc is the accuracy for all the trade in period t. However, since this measure has the same disadvantage as

DPIN base measure does (see in section 10.1), we also adjust it with trading volume.

$$Acc_{Vol} = \frac{\sum_1^m VB_{t,m}}{\sum_1^{m+n}(VB_{t,m} + VS_{t,n})}(P_t < P_{t+1}) + \frac{\sum_1^n VS_{t,n}}{\sum_1^{m+n}(VB_{t,m} + VS_{t,n})}(P_t > P_{t+1}) \tag{10}$$

where n and m are the numbers of profitable trades in period t. $VB_{(t,n)}$ and $VS_{(t,m)}$ are their volumes. We also divide the data sample by different market value as we did in WPC test.

Figure 8: The results of Profit Seeking Test



Note: The degree of accuracy is display on the Y-axis for both the upper and lower pannel. The numbers of on the X-axis denotes the ending time of each five-minute interval within the day.

Assuming the stock market is a zero-sum game with prefect market condition, active and passive sides in a trade should have both 50% of wining. However, our results in Figure 8 show that all the trades have the predict accuracy over 50%. This may suggest that active side in trading may have better short-term profitability. Furthermore, we can see that the first and last 30-minutes do have higher accuracy than other time. And smaller stocks have deeper U-shaped pattern than large stocks.

6 Conclusion

This Chapter shows the intraday pattern of volume, volatility, liquidity, level of informed trading and price discovery in China stock market by using high frequency data. The results show the intraday and overnight information flow could explain investors' preferences to trade more at the beginning and ending period of the day. Two robustness tests are implemented with supporting results. As the starting Chapter of this research, it introduces the preliminary statistics of our data and also enlightens our following research of modifying the VDPIN model in Chapter 2 and seeking motivations, as well as it influences of informed tradings in Chapter 3.

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Chapter 2

Research on Information Driven Trades in China

Abstract

We examine the information driven trades and informed traders' order size strategies in China's stock market. We find the aggregate U-shaped informed trading is not only explained by the time-of-day effect but is also related to the order size strategy, which is shown by intraday variations in the composition of small, medium, and large trades. The evidence of information predictability from early morning to market close and from late afternoon to the next day provides additional insights into the intraday informed trading pattern. We identify the non-negligible price impact (*PI*) of large trades and propose a modified model, *VDPIN-PI*, which better captures the trades with information advantage compared to the baseline model.

Key words: Information advantage; contrarian trades; information driven trades; camouflage; order size; intraday pattern; predictability; price impact

1 Introduction

One well-documented phenomenon about informed trades is that they concentrate at the opening, and sometimes the closing, period of the exchange (Madhavan et al., 1997; Barclay and Hendershott, 2003). Admati and Pfleiderer (1988) argue that, since the market opening and close are distinguished by the fact that they fall just after and before the exchange is closed, respectively, they may cause increased trading volume because of a rush to trade by informed and liquidity traders. Further, Gao et al. (2018) suggest that the intraday return predictability can be partially caused by late-informed trading near the market close to avoid overnight risk. Another strand of research focuses on the order submission strategies of informed traders. Kyle (1985) suggests that profit-maximising informed investors may attempt to camouflage their information and reduce the price impact by spreading trades over time. Barclay and Warner (1993) find that informed traders will concentrate on medium-sized trades, given their concerns such as costs related to regulatory requirements, delays and brokerage commission. In contrast, Barardehi et al. (2018) argue that aggressive market orders in large sizes may be used during high-liquidity times when the price impacts are small. The present study attempts to examine the trading strategies of informed traders in China's stock market, which is dominated by retail investors who are usually perceived to be irrational and impatient. To maximise their profits, do informed traders in China tend to behave cautiously and camouflage their trades or to trade aggressively, given the atmosphere of urgency and the likely consequence of high delay costs? In this study, we examine the presence of informed trading and informed traders' strategies concerning price impact and order size and offer three contributions to the related literature.

First, we propose an intuitive method for examining the price impact of influential trades. Then we develop a modified informed trading measure by considering the price impact. Second, we investigate the intraday informed trades in China's stock market and detect that these have an aggregated U-shape. After identifying the heterogeneous characteristics of informed trades from three trade size categories (small, medium and large), we discover that in addition to the time-of-day effect, the overall U-shape stems mainly from variations in the trade size composition. Third, to gain more insights into the right-side peak of the U-shape, we analyse the unexpected return predictability. Thus we discover that the late afternoon informed trading is motivated not only by information retained from the early morning but also by privileged access to private information supposed to arrive the next day, which provides additional explanation for the high informed trading at the opening and near the market close. The information advantage of informed traders suggest their power to forecast future stock returns, which explains the intraday return predictability documented in different markets and assets classes (Gao et al. (2018), Gao et al. (2019) and Zhang et al. (2020)). Our findings of intraday pattern of information-motivated trading also shed lights on information dissemination and price discovery in stock markets of developing countries.

A large body of literature is available on informed trading measures and the relevant trading strategies of informed traders. One such measure that Easley et al. (1996) proposed relies on trade imbalance, driven by information shock, to infer the probability of informed trading (PIN). Another measure, first proposed by Avramov et al. (2006) and then developed by Chang et al. (2014) and Chang and Wang (2019), is proxied by contrarian trades. The rationale for this proxy measure is that those who trade against the market, rather than engaging in herding, are akin to informed traders. It defines buy trades in the presence of negative unexpected returns and sell trades in the presence of positive unexpected returns as contrarian trades. Piotroski and Roulstone (2005) also establish insiders possessing superior information as contrarian traders who reverse the trajectory of past returns, sending signals that prices are under or overvalued. We conjecture that in China's market, where retail investors dominate, contrarian trades are likely executed by informed traders. Moreover, this proxy measure is easy to implement and can be applied to different trade size groups, and hence, it can be used to examine the order size strategies of informed traders.

In this study, we first use contrarian trades to represent informed trades, noted as the baseline volume-based dynamic probability of informed trading (baseline *VDPIN*). The overall probability of informed trading at each interval reflects the time-of-day effect of such trading. However, the estimated results cannot illustrate the strategies of informed traders on order size. This concern stems from their conflicting interests between the cost of large trade price impact and of information delay. To examine this trade-off, we employ the baseline *VDPIN* for each trade category of small, medium, and large sizes. The results suggest that the probabilities of informed trades for each trade category exhibit different intraday characteristics from the overall results. This inconsistency poses a challenge to the usual interpretation of the intraday U-shaped informed trades. Does the overall U- shape reflect only informed traders' preference to trade at the market opening and closing periods? The analysis of the trade size composition offers alternative explanations and prevents us from taking for granted that the time-of-day effect alone can explain the U- shape. We are motivated to further explore the causes of the overall higher percentage of informed trades at the two special periods. Thus, we compare the composition of the three trade size categories throughout the day and establish that the aggregate U-shape of informed trades is also explained by changes in the composition of small, medium, and large trades within the day. In addition, at daily opening and close, when informed trading is intensive, large trades are observed with a decrease in the average trade size but an increase in the proportion. Meanwhile, midsized trades show an increase in the trade size and the proportion. These results imply that large orders are split into medium-sized ones, perhaps because of informed traders' camouflage motive.

The subgroup results suggest that small and medium contrarian trades both demonstrate an intraday U-shaped pattern, whereas large contrarian trades display a reversed U-shape pattern (see Section 4.2). We conjecture that, without considering the substantial price impact of large trades, the baseline *VDPIN* may fail to capture some large informed trades and mistakenly include some uninformed contrarian trades instead. To examine this argument, for each trade size category we assess the trade price impact in two ways. Thus we find that large trades have a significantly higher price impact compared with small and medium trades. Hasbrouck (1991) measures the information content of stock trades as the ultimate price impact of the trade innovation and also finds that large trades have a larger price impact.

These findings lead to another aim of our research - to develop an informed trading measure that considers the price impact *(PI)*. Acknowledging the non-negligible price impact of large trades and its influence on unexpected returns, we first divide the time intervals with large trades into impact intervals and non-impact intervals. At impact intervals, we argue that contrarian trades are unable to capture the large informed trades because high information content is embodied in the unexpected returns. Specifically, a positive (negative) information shock manifests itself as positive (negative) unexpected returns. Therefore, non-contrarian trades actually represent the informed trades in impact intervals. We propose a modified model in which we adjust the baseline *VDPIN* for a large trade price impact within impact intervals and make no adjustment within non-impact intervals. The overall results of the modified model *VDPIN-PI* show a more pronounced U-shape of informed trading than that from the baseline *VDPIN*. To assess the effectiveness of the modification, we perform two robustness tests and find supportive evidence. First, an autocorrelation test shows a clear return reversal for those trades executed by uninformed traders measured by *VDPIN-PI*. This result is supported by the argument that price changes caused by (uninformed) liquidity trades should be reversed later (Campbell et al., 1993). Second, the results of an information advantage test suggest that a higher proportion of informed trades captured by *VDPIN-PI* than by the baseline measure has information advantage.

The remainder of this article proceeds as follows. Section 2 reviews the literature and Section 3 describes the data. Section 4 introduces the baseline model to capture informed trades, discusses trade size and their composition variations, and reports the estimation results. Section 5 examines the price impact of different trade size groups and develops the informed trading measure (*VDPIN-PI*) modified for price impact. Section 6 extends the analysis on the unexpected return predictability, and Section 7 performs robustness tests. Section 8 concludes.

2 Literature Review

Informed traders play an important role in stock price discovery by incorporating information into stock prices and subsequently improving the market efficiency (Piotroski and Roulstone, 2004). One strand of research aims to discern the disparate characters and influences of informed trades from liquidity trades. For example, Campbell et al. (1993) argue that informed trades and liquidity trades should differ in that liquidity trades will cause a temporary price change that will subsequently be reversed. In contrast, price reversals are not expected to occur following the price changes generated by informed trades. Conversely, Admati and Pfleiderer (1988) examine the interacting strategic decisions of informed traders and discretionary liquidity traders (who can time their trading) and develop a theory that states discretionary liquidity trading is typically concentrated and informed traders trade more actively in periods when liquidity trading is concentrated. Meanwhile, liquidity traders also benefit from the increased entry of informed traders who compete with each other, which typically improves the welfare of liquidity traders. Admati and Pfleiderer (1988) argue that their theory of the strategic behaviour of liquidity traders and informed traders provides a partial explanation for the intraday U-shaped patterns of volume and price variability.

Other scholars are interested in informed investors' strategic choices of order size. Some models indicate that informed traders prefer to trade large amounts at any given price because they face competition from other informed traders and the privacy of their information could be short-lived (Easley and O'Hara, 1987; Grundy and McNichols, 1989; Holthausen and Verrecchia, 1990; Kim and Verrecchia, 1991). Alternative theories suggest that the expected price impact of large trades (i.e., price concessions) increases with trade size, and profit-maximising informed investors may attempt to camouflage their information by spreading trades over time (Kyle, 1985). To address more specifically informed investors' trade-size choices, Barclay and Warner (1993) analyse these informed investors' trade-off between the cost of price impact and of information delay, the possibility of detection and prosecution of illegal trading on private information and their concern about the brokerage commission cost. They hypothesise that informed traders will concentrate their trades in medium sizes (i.e., stealth trading hypothesis). The price impact of large trades is also documented in other studies. For example, Chan and Fong (2000) find a significant return impact of order imbalance, and that the order imbalance in the large trade size category affects the return more than that in smaller trade size categories for stocks traded on the New York Stock Exchange (NYSE). As regards the London Stock Exchange (LSE), Sun and Ibikunle (2017) also find a positive (negative) relationship between informed trading and the permanent price impact of block purchases (sales), thereby suggesting that private information is impounded via block trading on this exchange.

Several models have been proposed in the literature to measure informed trades in the securities market. For example, Roll (1988) is the first to suggest that price non-synchronicity (or firm-specific return variation) can be a suitable proxy for private information. Easley et al. (1996, 1997) develop a structural market microstructure model to measure the probability of informed trading (PIN), based on observable data on the number of buys and sells from the trading process. Chen et al. (2007) apply both approaches in examining price informativeness and investment sensitivity to stock price and suggest that the PIN measure of Easley et al. (1996, 1997) may capture the source of information (trading activities of informed traders) reflected in price, whereas price non-synchronicity may capture the result of this information on the price. Duarte and Young (2009) indicate that the PIN of Easley et al. (1996, 1997) can actually be decomposed into two components and that only one component (adjusted PIN) measures asymmetric information whereas the other (probability of symmetric order flow shock) measures illiquidity effects unrelated to information asymmetry. However, a problem associated with the PIN of Easley et al. (1996, 1997) is that it may be sensible to estimate certain parameters in the PIN model over a long macro horizon. Over long horizons, it is likely that the actual effects of short-lived information may be diluted or masked by other factors (Chang et al., 2014). Other models that do not require intermediate numerical estimation of non-observable parameters include those by Easley et al. (2012) and Chang and Wang (2019).

Some studies have examined the rationality of investors by studying herding and contrarian behaviour in financial markets. For example, Avery and Zemsky (1998) indicate that information cascades - when it becomes rational to ignore one's own private information and instead follow one's predecessors' decisions (herding) - cannot occur in a simple sequential asset market because a flexible market price incorporates all publicly available information. To test this theory, Drehmann et al. (2005) designed an internet experiment based on a sequential asset market with privately informed traders. They do not find evidence of herding, which supports Avery and Zemsky's (1998) prediction. In contrast, they find that informed subjects frequently act as contrarians. Following previous research on rational and irrational investors (Friedman, 1953), positive feedback investment strategies (e.g. Cutler et al., 1990; DeLong et al., 1990) and herding investors (Froot et al., 1992), Avramov et al. (2006) conjecture that herding or positive feedback behaviour represents uninformed trades, whereas contrarian trades are akin to informed trades.

3 Data and Descriptive Statistics

This study is based on quote and trade data from China's stock market. Compared with developed markets, this market is believed to have less effective implementation of regulations on corporate disclosure and insider trading. Further, its market participant composition differs in that it has more retail investors and fewer institutional investors. Given the higher expected level of information asymmetry, it is worth examining China's market to study informed trading behaviour, which may differ from that of other developed markets. The sample data are obtained from the Wind database[1], consisting of 300 constituent stocks of the CSI300 index. The CSI300 stocks are from the Shanghai and Shenzhen Stock Exchanges and account for about 60% of China's overall stock market capitalisation. Our sample includes data from January 2012 to December 2014. Buyer-and seller-initiated trades are indicated for each trade. The Shanghai and Shenzhen Stock Exchanges both employ the call auction trading mechanism from 9:15 to 9:30 am to open the market and Shenzhen Stock Exchange also employs this mechanism from 14:57 to 15:00 pm to close the market. We exclude all call auction periods of the two exchanges from our sample because quote and trade data are not available. Finally, our dataset includes all transactions of the 300 stocks during the continuous auction periods of 9:30 to 11:30 in the morning and 13:00 to 15:00 (13:00 to 14:57 for Shenzhen Stock Exchange) in the afternoon during the three years.

[1] Website of Wind Database: www.wind.com.cn

The sample period of 729 business days has 1,222.19 million trades in total, including 643.48 million (52.65%) buyer-initiated (buy) trades and 578.71 million (47.35%) seller-initiated (sell) trades. We stratify all trades into three trade size groups according to the classification by Straight Flush - the local trading platform most widely used by market participants in China.

All trades are labelled as small, medium or large trades, depending on whether the trading volume is below 20,000 shares, between 20,000 and 100,000 shares, or above (including) 100,000 shares, respectively. The individual stock returns are calculated over five-minute intervals as changes in the midpoints of the bid-ask spread to avoid any bid-ask bounce. Each trading day has 48 five-minute intervals throughout the continuous auction periods.

The upper panel of Table 1 summarises the statistics of each trade classification. The trades are dominated by small trades. The lower panel of Table 1 provides the summary statistics of the five-minute returns. The maximum and minimum returns are not reported because they are capped by ±10% of the daily price limits applied in China's stock market. The average interval return is $2.41*10^{-6}$, which is positive over the whole sample. The positive and negative returns have similar standard deviations and kurtosis, but skewness of opposite sign.[2]

Table 1
Summary statistics on trades and interval returns

Trades of small, medium, and large sizes			
	No. of trades (million)	No. of trades (%)	Vol. of trades (%)
Small	926.84	75.88	52.85
Medium	279.33	22.87	35.96
Large	15.34	1.25	11.19
Total	1,221.51	100.00	100.00

5-minute interval returns					
	Mean	S.D.	Median	Skewness	Kurtosis
All	$2.41* 10^{-6}$	0.0031	$8.31* 10^{-7}$	-0.28	5.10
Positive	$4.29* 10^{-5}$	0.0029	$4.61* 10^{-5}$	0.37	4.97
Negative	$-4.27* 10^{-5}$	0.0028	$-4.48* 10^{-5}$	-0.41	5.21

Note: The upper panel presents the descriptive statistics of small, medium and large trades from January 2012

[2] We also divide each trading day into sixteen 15-minute intervals and analyse the intraday pattern of informed trading. Similar but less prominent results are obtained compared with those for the five-minute interval. We report the five-minute interval results, which allow us to have more insights and understanding of information occurrence, informed trading behaviour and the market in general. The analysis results for the 15-minute intervals are not reported but are available upon request.

to December 2014. The 'No. of Trades' column reports the total number of trades in each trade size category. The 'No. of Trades (%)' and 'Vol. of Trades (%)' columns report the percentage of the number of trades and trading volume relative to the total trades for each category. The lower panel presents the summary statistics on the five-minute interval returns for all 300 stocks over the sample period. The statistics were first computed for individual stocks over time and then averaged for each return group: all returns, positive returns, and negative returns.

4 Baseline *VDPIN* Model, Trade Size, and Composition

In this section, we construct a baseline *VDPIN* model and employ it to estimate the probability of informed trading in the whole sample. To gain further insights into informed trading strategies, we divide the whole sample into three different trade size categories and apply the baseline model to each of them.

4.1 Baseline *VDPIN* Represented by Contrarian Trades

Avramov et al. (2006) suggest that contrarian trades (according to the direction of unexpected returns) are akin to informed trades, which is supported by the empirical findings of their own research as well as that of Chang et al. (2014) and Chang and Wang (2019). The intuition and explanations are that the unexpected return over an interval (after excluding the influence of past information and some routine day and interval effects) reflects the price movement direction within the current interval. For example, a positive unexpected return over an interval is a result of upward price movement. Then sells in this interval are defined as contrarian informed trades because they do not follow the broad market and are more likely driven by private information not known to the market yet. Following Avramov et al. (2006), we first isolate the unexpected component of returns as the residuals from the following regression in Equation (1), and then designate buy (sell) trades in the presence of negative (positive) unexpected returns as informed (contrarian) buys (sells):

$$R_{i,j} = \sum_{k=1}^{5} \gamma_{1i,k} D_k^{Day} + \sum_{k=1}^{48} \gamma_{2i,k} D_k^{Int} + \sum_{k=1}^{12} \gamma_{3i,k} R_{i,j-k} + \varepsilon_{i,j} \tag{1}$$

where $R_{i,j}$ is the five-minute interval return of stock i at intraday interval j (j = 1, 2, ..., 48), D_k^{Day} is a dummy variable measuring the day-of-week effect, and D_k^{Int} is a dummy variable measuring the effect of a particular five-minute interval. Thus, the residual $\varepsilon_{i,j}$ captures the unexpected return of stock i at interval j, after accounting for average day-of-week effects, average interval-of-day effects and return autocorrelation effects.[3] In a given interval, those

[3] The serial dependence on returns is caused by the lagged adjustment to information, exchange-

trades that buy/sell in the same direction as the sign of the residual demonstrate herding behaviour and are classified as uninformed trades. By contrast, those trades against the sign of the residual are termed contrarian trades and are classified as informed trades.

Our baseline measure $VDPIN_{Base_{i,j}}$ for stock i in each five-minute interval j is specified in Equation (2). Chang et al. (2014) note that their dynamic probability of informed trading (*DPIN*) measure fails to capture the widely known U-shaped intraday pattern of informed trading, which is successfully documented by their $DPIN_{SIZE}$ measure with size effects incorporated. This finding suggests the importance of considering the size effect in the informed trading measure; thus, we use trading volumes (or shares traded), rather than the number of trades, to develop our baseline *VDPIN* measure.

$$VDPIN_{Base_{i,j}} = \frac{VB_{i,j}}{VT_{i,j}}(\varepsilon_{i,j} < 0) + \frac{VS_{i,j}}{VT_{i,j}}(\varepsilon_{i,j} \geq 0) \tag{2}$$

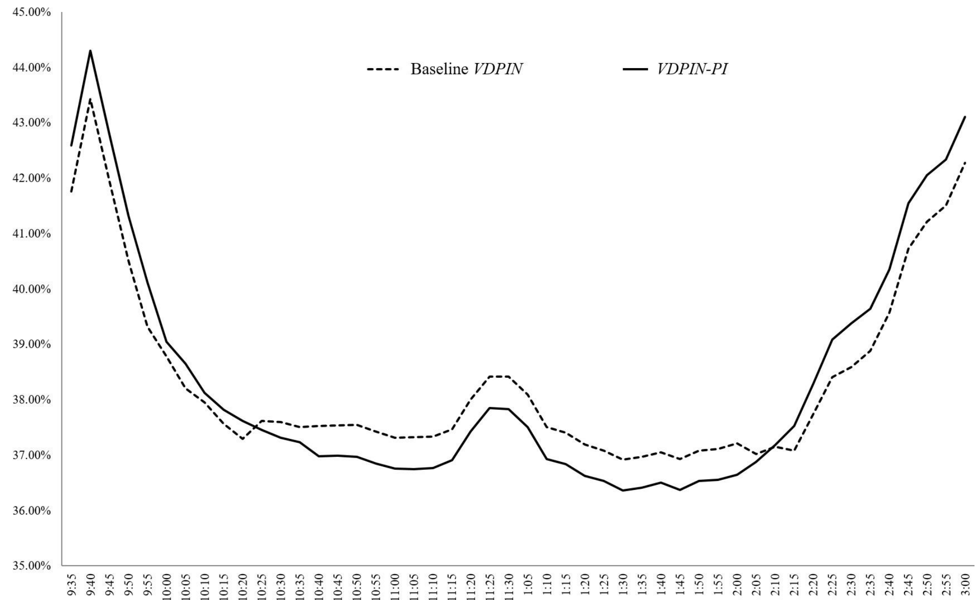
where $VB_{i,j}$ is the total volume of buys for stock i at interval j, $VS_{i,j}$ is the total volume of sells for stock i at interval j and $VT_{i,j}$ is the total volume of trades (buys as well as sells) for stock i at interval j. The percentage of informed (contrarian) buys (or sells) is denoted as $VB_{i,j}/VT_{i,j}$ $(\varepsilon_{i,j} < 0)$ (or $VS_{i,j}/VT_{i,j}$ $(\varepsilon_{i,j} \geq 0)$). $\varepsilon_{i,j} < 0$ is an indicator variable that equals 1 when the unexpected return is negative, and 0 otherwise (defining contrarian buys), and $\varepsilon_{i,j} \geq 0$ is an indicator variable that equals 1 when the unexpected return is positive, and 0 otherwise (defining contrarian sells).

By aggregating $VDPIN_{Base_{i,j}}$ across the 300 stocks over three years for each five-minute interval, the intraday dynamics of informed trades can be displayed as the dashed line in Figure 1. Consistent with the widely documented findings in the literature, informed trading shows an overall U-shaped intraday pattern. However, we note a spike at the opening periods, with the second five-minute interval exhibiting higher probability of informed trading than the first five-minute interval. This spike occurs primarily because China's stock exchanges apply a call auction (9:15 to 9:30 am) to open the market prior to the formal opening of the continuous market at 9:30 am. Part of the information accumulated overnight is already disseminated into prices in the call auction, which provides feedback that requires time for other participants to reflect. Evidence of the call auction's contribution to price discovery and market quality has also been found for the London Stock Exchange (Ellul et al., 2005) and the Nasdaq (Pagano

mandated price smoothing and other market microstructure imperfections (Hasbrouck, 1991).

et al., 2013).

Figure 1. Intraday informed trades measured by baseline *VDPIN* and *VDPIN-PI*



Note: This figure shows the percentages of informed trades for each interval aggregated across all stocks and over all trading days from the baseline *VDPIN* and modified *VDPIN* (*VDPIN-PI*) models. The time displayed on the X-axis denotes the ending time of each five-minute interval within a day.

4.2 VDPIN Measure for Trades of Different Sizes

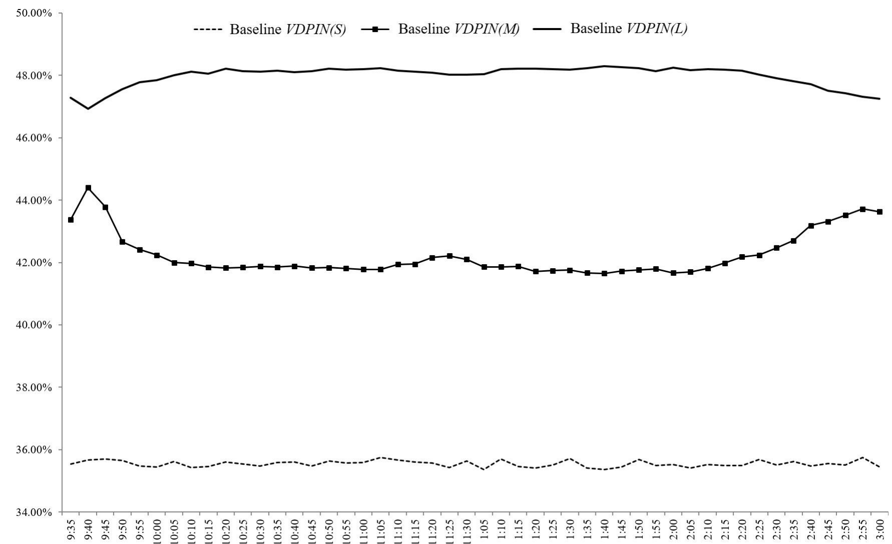
To gain insights into the order size strategies of informed traders, we consider a finer classified measure of informed trades by applying the baseline *VDPIN* to each trade category of small, medium, and large trade sizes, as in Equation (3):

$$VDPIN_{Base_{i,j}}(TS) = \left[\frac{VB_{i,j}}{VT_{i,j}}(\varepsilon_{i,j} < 0) + \frac{VS_{i,j}}{VT_{i,j}}(\varepsilon_{i,j} \geq 0)\right](TS) \tag{3}$$

where $TS = S \text{ or } M \text{ or } L$ indicates small, medium, and large trade size, respectively. The right side of Equation (3) specifies the percentage of contrarian trades within its own trade size category at each interval. For instance, when TS is equal to L, $VDPIN_{Base_{i,j}}(L)$ refers to the percentage of large-sized contrarian trades in relative to the subgroup of large trades for each stock i and at each interval j.

The aggregated percentages of informed trades for the three trade size categories over the 48 five-minute intervals are presented in Figure 2. They show distinct features and their pattern differs from the overall pattern presented in Figure 1. The percentages of informed trades increase with trade sizes, wherein the highest percentage is of the large-sized trades. None of the intraday variations from any trade category is as much as that from the overall trades. Small informed trades demonstrate the least variation throughout the day. For large informed trades, minor declines appear at the beginning and end of the day. The subgroup of medium-sized is the only one showing similar characteristics to the overall trades, but with a flatter U-shape.

Figure 2. Intraday informed trades measured by baseline *VDPIN* for small, medium, and large trades



Note: Figure shows the intraday pattern of informed trades measured by the baseline *VDPIN* for different trade size categories. The three lines represent small, medium, and large informed trades. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day.

In addition, we can observe that at the beginning and end of the day, the percentage of informed trades falls mainly in the medium-sized subgroup. The various levels and patterns of informed trading between subgroups and their deviations from the overall result cast doubt on the general perception that the U-shape is explained by only the time-of-day effect. The attempt to discover the attributes of the deeper U-shape from the overall trades leads us to further examine the relative proportions of the three size groups.[4]

The left side of Figure 3 presents the proportion of small, medium, and large trades, in terms of both number of trades and trading volume, in all trades within the day. The large- and medium-sized trades show a U-shape, whereas the small trades exhibit a reversed one, which means that a lower proportion of small-sized trades occurs at the beginning and end of the day. This implies that during these periods, (informed) investors use more medium- or even large-sized orders to acquire positions and minimise information delay

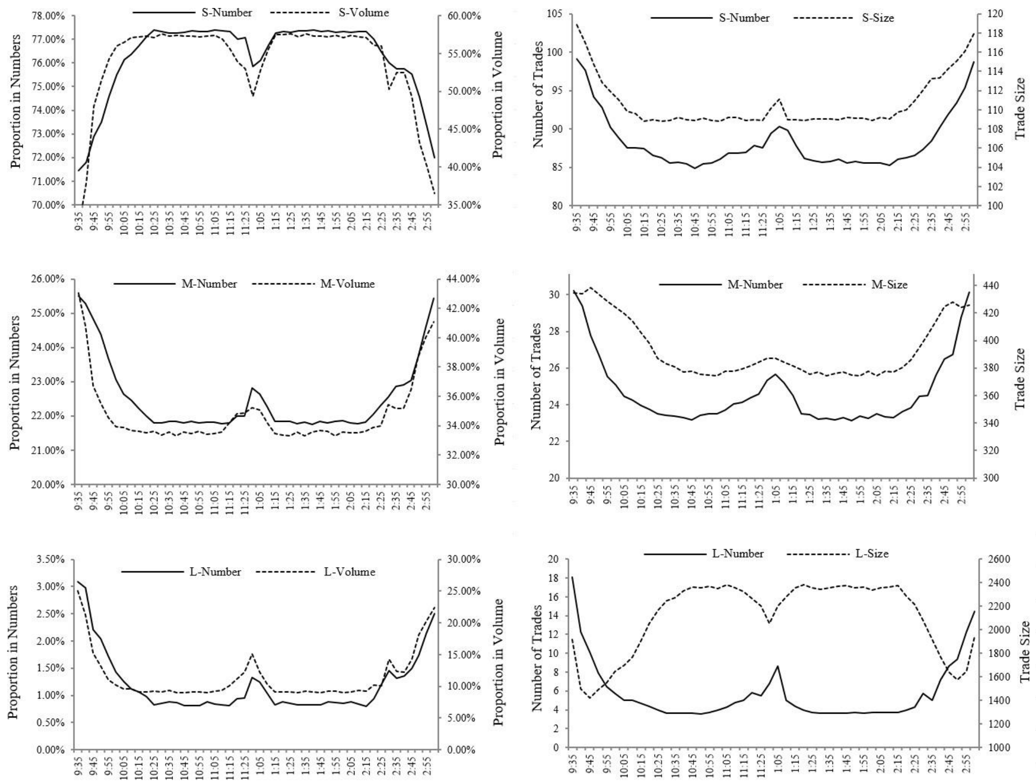
[4] Detailed results of the baseline *VDPIN* measure for trades of different sizes are reported (together with the results of the *VDPIN-PI*) in Table 3 for comparative analysis.

costs. Notably, that the lower proportion of small trades does not mean these trades are less present over these intervals - rather, these are accompanied by a higher absolute number of trades.

The right side of Figure 3 displays the average number of trades and trade sizes at each five-minute interval for the three size categories. Small-sized trades, similar to medium- and large-sized trades, peak in terms of the number of trades at the day beginning and end. Different from the similar patterns observed for the number of trades, the average trade sizes show distinct features among these categories. The key difference is as regards large trades, because they present a reversed U-shape, opposite to the ones from the small and medium trades. This finding suggests that investors who trade in large sizes choose to submit orders with smaller sizes at the beginning and ending period, which may be attributed to the camouflage motive and stealth trading of informed traders (Kyle, 1985; Barclay and Warner, 1993). The average sizes in the first and last 10 minutes are higher compared with those in the other intervals at the beginning and end of the day. This result could be explained by considering that the delay cost outweighs the price impact cost faced by informed traders or that large discretionary liquidity traders concentrate their trades at these particular periods (Barclay and Warner, 1993; Madhavan et al., 1997).

Figure 3 reinforces that the trades of all three subgroups increase at the beginning and end of the day, but the medium and large trades do so more than the small trades. It is equally noteworthy that while the number and volume of large trades increase at the opening and end of the day, the percentage of informed trades in the large size category shows minor declines. Does this simply reflect a higher proportion of large-sized liquidity trades during these periods? Otherwise is there any problem with the baseline *VDPIN* in measuring large-sized informed trades, which have a substantial price impact? We address this issue in the next section.

Figure 3. Intraday average numbers of trades, trade sizes and intraday proportions for small, medium, and large trades



Note: The left-side panels of this figure show the composition for small, medium, and large trades within a day. They represent the average proportions of each trade size group to all trades in terms of both number of trades and trade volume at each interval. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day. The right-side panels show the average number of trades and trade sizes for small, medium and large trades. Small, medium and large trade categories are displayed at the upper, middle, and lower panels separately. The scale for average numbers of trade is displayed on the left Y-axis (S-Number, M-Number and L-Number). The scale for average trade sizes is displayed on the right Y-axis (S-Size, M-Size and L-Size) in the unit of 'round block', which represents 100 shares. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day.

The stronger variation in the trade composition proportions (in the left side of Figure 3) for each trade subgroup compared with those in Figure 2 provides an underlying explanation to the overall pattern of informed trades observed in Figure 2. The more pronounced U-shape of the total informed trades is mainly caused by the increased medium trades that generally contain more informed trades than the other two subgroups. In addition, it refutes the general perception that all three trade subgroups show a U-shape. The slightly higher informed trading percentage at the opening and close observed for the medium-sized subgroup also lends support to the camouflage and stealth trading hypothesis as regards informed traders.

5 Large Trade Price Impact and *VDPIN-PI*

An unconventional reversed U-shape is found for large informed trades, as discussed in Section 4. The analysis in this section provides insights regarding why the baseline *VDPIN* may fail to capture informed trades of large sizes and instead may mistakenly include some non-informed contrarian trades because of the effect of price impact. The baseline *VDPIN* builds on the implicit assumption that informed trades do not have a significant price impact. However, large trades are more likely to contain information and have a price impact, which will be transmitted into the related contemporaneous unexpected returns. Therefore, unexpected returns in intervals with large trades can proxy for the information shock carried by large trades. This transmission mechanism is also documented by Hasbrouck (1991). He develops a framework that relates the trade (via the inferred private information) and the quote revision and finds a higher price impact for large trades. Price impact is also considered in informed trading modelling by Kitamura (2016). Hung and Lien (2019) suggest that higher trading aggressiveness, based on trader's own private information, will more quickly push stock price to its new equilibrium level. They find trading aggressiveness is positively related to price impact, which implies the importance of considering price impact when measuring informed trading. Through the following examinations, we aim to illustrate the non-trivial price impact, the influence on unexpected returns, and the implications for the model modification.

5.1 Large Trade Price Impact

Next, we examine our conjecture regarding the large trade price impact and its effect on the informed trades proxy with contrarian trades, using two methods. For both methods, intervals are separated into two groups, depending on the presence or absence of large trades in the interval. In total, there are 581,057 intervals with, and 9,287,598 intervals without, large trades. In the first method, we investigate whether the price impact of trades differs in two interval groups. Following the literature (see, e.g. Sun and Ibikunle (2017)), the price impact is measured at a five-minute frequency with Equation (4) and Equation (5):

$$Percentage\ price\ impact_s(PPI_s) = \frac{2D_s(M_{s+5} - M_s)}{M_s} \tag{4}$$

$$Average\ PPI_{i,j} = \frac{1}{N} * \sum_{s=1}^{N} PPI_s \tag{5}$$

where PPI_s denotes the percentage price impact for trade s, D_s is a dummy variable that indicates the direction of trade s and equals 1 when trade s is a buyer-initiated trade and -1 when trade s is a seller-initiated trade, M_s is the bid-ask midpoint at the time that trade s occurs, M_{s+5} is the bid-ask midpoint five minutes after trade s, $Average\ PPI_{i,j}$ refers to the average percentage price impact for trades of stock i at each interval j and N denotes the total number of trades for stock i at each interval j. Table 2 demonstrates the significant price impact caused by large trades, for both methods. The average percentage price impact of trades at intervals with large trades (0.0927%) is more than three times of that without large trades (0.0254%), with the difference being significant at 1% levelusing the Z-test.[5]

Table 2
Percentage price impact, unexpected return, and trade imbalance

	Intervals with large trades		Intervals without large trades	
$Avg\ PPI_{i,j}$	0.0927%		0.0254%	
	$TI_{i,j} \geq 0$	$TI_{i,j} < 0$	$TI_{i,j} \geq 0$	$TI_{i,j} < 0$
$\varepsilon_{i,j} \geq 0$	74.13%	25.87%	60.54%	39.46%
$\varepsilon_{i,j} < 0$	20.51%	79.49%	36.03%	63.97%

Note: In the upper panel of the table, the row of '$Avg\ PPI_{i,j}$' presents the average percentage price impact of trades for stock i at each interval j, according to Equation (4) for intervals with and without large trades. The lower panel demonstrates the proportions of positive and negative unexpected returns and the interactions between the unexpected return and trade imbalances for both interval categories (with and without large trades). $\varepsilon_{i,j} \geq 0$ and $\varepsilon_{i,j} < 0$ refer to the direction of unexpected returns in each interval. The columns of '$TI_{i,j} \geq 0$' and '$TI_{i,j} < 0$' represent the percentages of the direction of trade imbalance given the sign of unexpected return. Thus, the numbers on the diagonal and off the diagonal represent the percentage of intervals that have the same or opposite signs to TI and ε.

In the second method, the previously detected higher price impact from large trades is further examined to determine the potential influence on price changes and the unexpected returns. Intuitively, the net effect of the trade imbalance between buys and sells will be realised on the price change.[6] For instance, the trade imbalance of net buys is associated with a price increase and positive unexpected returns. Thus we study the directional relationships between the trade imbalance and unexpected return and compare the results at intervals with and without large trades. These results suggest the existence of an influential price impact of large trades if the directional relationship varies on the inclusion of large trades. Following Sun and Ibikunle (2017), we introduce trade imbalance in Equation (6) as follows:

$$TI_{i,j} = VB_{i,j} - VS_{i,j} \tag{6}$$

[5] Given the prevalence of medium-sized trades, it is not sensible to further separate the intervals between with and without midsized trades.

[6] To clarify, the directional relationship in this study refers to the consistency of the signs of two variables, $TI_{i,j}$ and $\varepsilon_{i,j}$.

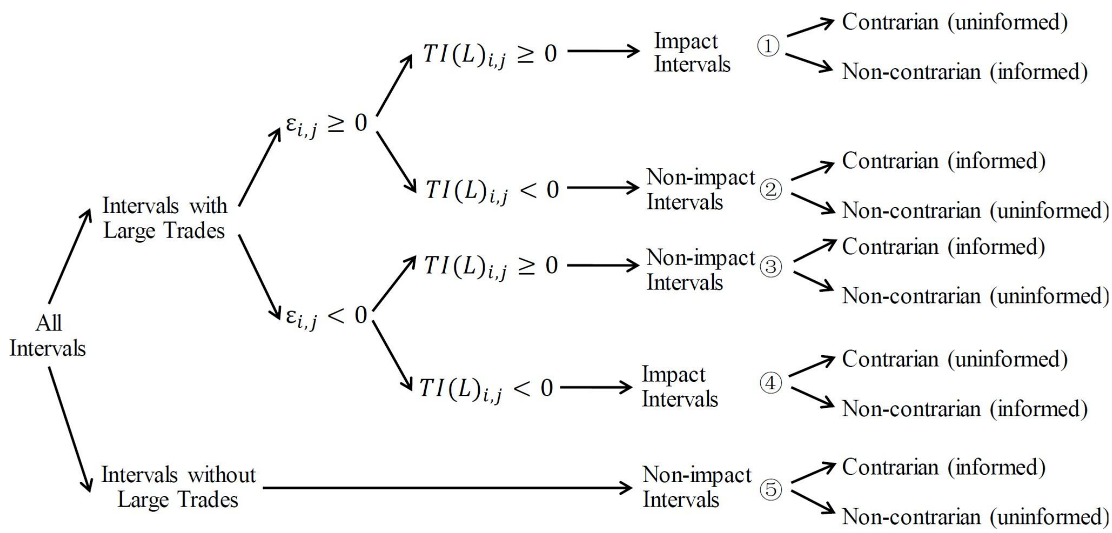
where $TI_{i,j}$ denotes the trade imbalance factor for stock i at interval j, $VB_{i,j}$ is the total volume of all buyer-initiated trades and $VS_{i,j}$ is the total volume of all seller-initiated trades in the same interval.

The lower panel of Table 2 reports the relationship between TI (trade imbalance) and ε (unexpected return) for intervals with and without large trades. It shows that the values on the diagonal are higher than those off the diagonal for all intervals. This can be inferred from the effect of net buy (sell) pressure on price change and hence the sign of the relevant unexpected return. However, for intervals with large trades, TI and ε of the same sign (74.13% and 79.49%, respectively) occur more frequently than these do for intervals without large trades (60.54% and 64.97%, respectively). This result suggests that large trades have a much higher impact on prices; hence, the signs of unexpected returns in those intervals are likely to be driven by (and to be consistent with) the trade imbalance. Therefore, if informed traders submit large orders, those large trades with price impact would present as non-contrarian trades. For example, upon the arrival of positive news in a given interval, small- and medium-sized informed buys may have no substantial impact on prices. These buys would be identified as informed contrarian buys under the baseline specification. However, with the same positive information, if instead a very large sized order is submitted, this informed buy may exert a dramatic positive impact on the price, and the unexpected return estimated for this interval would appear to be positive. In this case, this large informed buy would not appear to be contrarian and would be missed in the baseline *VDPIN* measure. Worse, the baseline *VDPIN* measure would mistakenly capture sells as informed trades since sells show as contrarian trades. This explains why a reversed U-shaped pattern for large trades is observed from the baseline model in Figure 2. Thus, we modify the informed trading measure by incorporating the price impact factor. In addition, even for the intervals with large trades, not all trade imbalances align with the directions of unexpected returns. This observation reflects informed traders' order size adjustments to available liquidity; that is, not all large trades will cause an influential price impact.

5.2 VDPIN Modification with Price Impact

Given the substantial price impact of large trades, we develop the modified *VDPIN* model by contrasting the trade imbalance of large trades and unexpected returns. The model development is demonstrated with a tree diagram of five interval scenarios in Figure 4. All intervals are first divided into ones with and without large trades. For intervals with large trades, when unexpected returns (ε) and the trade imbalance of large trades $TI(L)$ have the same sign, we propose this interval to be the impact interval. Therefore, the intervals under scenarios ① and ④ represent the intervals with a large trade price impact (impact intervals). In contrast, when ε and $TI(L)$ have different signs, we designate these intervals to be non-impact intervals. Scenarios ② and ③ represent non-impact intervals. Considering the lower impact of small and medium trades, we perceive intervals without large trades as non-impact intervals under scenario ⑤.

Figure 4. Tree diagram of impact and non-impact intervals



Note: $TI(L)_{i,j}$ is the trade imbalance of large trades for stock i at interval j; $TI(L)_{i,j} = LVB_{i,j} - LVS_{i,j}$, where $LVB_{i,j}$ is the sum volume of all large buy trades and $LVS_{i,j}$ is the sum volume of all large sell trades.

Through distinguishing the price impact of large trades, our modified measure of informed trades uses contrarian trades only for non-impact intervals ②, ③ and ⑤ indicated in Figure 4. For impact intervals ① and ④, non-contrarian trades are used to represent informed trades. We admit that not all the non-contrarian trades in the impact intervals are informed trades. Nevertheless, the large trades with a price impact in these intervals are more likely to be informed trades, which should not be left out. In summary, the modified measure that incorporates the large trade price impact (*VDPIN-PI*) is described in Equation (7):

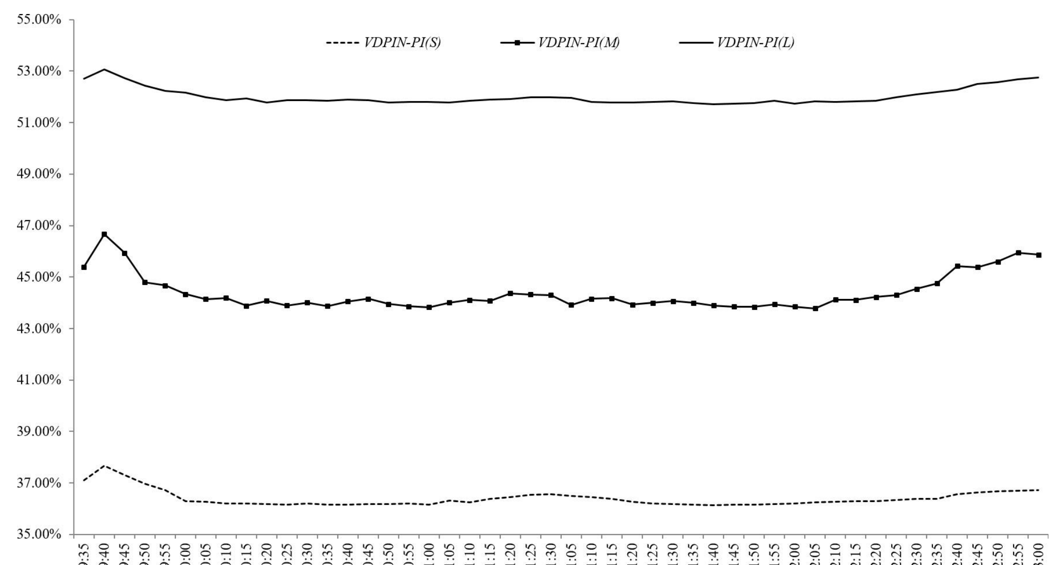
$$VDPIN-PI_{i,j} = \left[\frac{VB_{i,j}}{VT_{i,j}}(\varepsilon_{i,j} < 0) + \frac{VS_{i,j}}{VT_{i,j}}(\varepsilon_{i,j} \geq 0)\right](②③⑤)$$

$$+\left[\frac{VB_{i,j}}{VT_{i,j}}(\varepsilon_{i,j} \geq 0) + \frac{VS_{i,j}}{VT_{i,j}}(\varepsilon_{i,j} < 0)\right](①④) \quad (7)$$

By aggregating *VDPIN-PI* over all stocks and the whole sample period, the intraday informed trades over the 48 five-minute intervals is shown (as the solid line) in Figure 1.The informed trades exhibit a more prominent U-shape compared with that of the base- line *VDPIN*, thereby implying that the modified *VDPIN* captures more informed trades concentrating at the opening and closing periods of the day. Beyond the difference at the overall level, it is of particular interest to note the influence of the modification on each trade size category, especially for the large trades.

Figure 5 reports the intraday pattern of informed trades measured by the *VDPIN-PI* for each trade size category. Distinct changes are observed in the subgroup results compared with those in Figure 2. We can see a slight U-shape for the large trades, whereas the result from the baseline model shows a reversed U-shape. Moreover, a U- shape emerges for small trades, but no pattern is observed from the baseline *VDPIN*. These changes are mainly attributed to the inclusion of informed trades omitted in the baseline *VDPIN* measure. An anatomy of the changes is illustrated in Table 3 by breaking down the informed trades into each trade size group, compared with their counterparts from the baseline measure.

Figure 5. Intraday informed trades measured by *VDPIN-PI* for small, medium and large trades



Note: This figure shows the intraday informed trades measured by the *VDPIN-PI* for different trade size categories. The three lines represent small, medium and large informed trades. The time displayed on the X-axis denotes the ending time of each five-minute interval within the day.

Comparing the results of the two models, we observe an overall decrease in the percentage of informed trades identified by the *VDPIN-PI* in terms of number of trades (from 44.28% to 43.86%). However, the volume of informed trades reported by the *VDPIN-PI* increases (from 41.83% to 43.99%). Through scrutinising the changes in results from the baseline to the modified model, we find that the small size category experiences a drop in the number of informed trades (from 45.06% to 43.86%), but an increase in the volume of trades (from 40.09% to 41.74%). This result implies a higher average size of informed trades in the small-sized subgroup. In contrast, for the large-sized category, we identify a significant increase in the number of informed trades (from 40.12% to 57.54%), yet less so in the volume (from 47.81% to 52.59%). This result suggests that the average size of large informed trades decreases. The least change occurs in the medium-sized category. Combining these observations, we conclude that in the *VDPIN-PI* model trades with information tend to converge to the medium trade size, which lends further support to the camouflage argument of Kyle (1985) and the stealth trading hypothesis of Barclay and Warner (1993). Meanwhile, the size changes discovered in the informed trades provide further support for constructing the measures using the volume rather than the number of trades.

Table 3
Informed trades of *VDPIN* and *VDPIN-PI* across trade sizes

	No. of Trades (Million)	No. of Trades in Each Category (%)	Vol. of Trades in Each Category (%)
	Informed trades by baseline *VDPIN*		
Small	417.63	45.06	40.09
Medium	117.09	41.92	42.53
Large	6.15	40.12	47.81
Total	540.88	44.28	41.83
	Informed trades by *VDPIN-PI*		
Small	406.51	43.86	41.74
Medium	120.39	43.10	44.62
Large	8.83	57.54	52.59
Total	535.73	43.86	43.99

Note: This table summarises the informed trades captured by the baseline *VDPIN* and *VDPIN-PI* in each trade size category (small, medium, large and all trades). The 'No. of Trades (Million)' column reports the number of informed trades in each trade size category. The 'No. of Trades in Each Category (%)' reports the proportion of the number of informed trades in each trade size category to total number of trades in that category. The 'Vol. of Trades in Each Category (%)' column reports the proportion of the volume of informed trades in each trade size category to total trading volume in that category. The upper panel on the informed trades is estimated by the baseline *VDPIN*, and the lower panel reports the results of the *VDPIN-PI*.

6 Predictive Regression Analysis on the Information at Market Close

The literature generally suggests that the opening session of a trading day embeds information accumulated overnight, which explains the formation of the left-side peak of the intraday U-shaped pattern of informed trading. Yet, the formation of the right-side peak is less understood. Gao et al. (2018) document the intraday predictability of the last half-hour returns by using data on the first half-hour returns, which they find is supported not only by the infrequent portfolio rebalancing theory but also by the model of late-informed trading. Investors who receive information late or are slow in processing information will act before the market close when liquidity is high. However, we consider this argument merits further investigation. Do informed traders in the last half-hour trade only on the information retained from the early morning? Kurov et al. (2019) find that prices beginto move in the 'correct' direction before a macroeconomic news announcement. They suggest that some traders have private information about macroeconomic fundamentals. The source of their private information may be information leakage, their superior forecasting of public information or their proprietary information collection. Kaniel et al. (2012) and Campbell et al. (2009) document pre-announcement informed trading not only around the macroeconomic news, but also on corporate news. Given the aforementioned discussion, we examine the attributes of the information near the market close by testing the unexpected return predictability from market open to market close as well as from market close to the next day. Considering the high percentage of informed trading within the half-hour before and after market close in Figure 1, we analyse the predictive regressions at the half-hour frequency.

First, to examine the intraday predictability we focus on how the last half-hour unexpected return is predicted by that of the first half-hour using Equation (8).

$$\varepsilon_{i,14:30-15:00} = \alpha_1 + \beta_1 \varepsilon_{i,9:30-10:00} + \epsilon_{i,14:30-15:00} \tag{8}$$

where $\varepsilon_{i,14:30-15:00}$ ($\varepsilon_{i,9:30-10:00}$) denotes the unexpected return of stock i spanning from 14:30 to 15:00 (from 9:30 to 10:00). It is calculated by Equation (1) adjusted for half-hour frequency.

To assess the predictability of the unexpected return from the last half-hour to the next day, we estimate Equation (9).

$$\varepsilon_{i,15:00-10:00(+1),} = \alpha_2 + \beta_2 \varepsilon_{i,14:30-15:00} + \epsilon_{i,15:00-10:00(+1)} \tag{9}$$

where $\varepsilon_{i,15:00-10:00(+1)}$ ($\varepsilon_{i,14:30-15:00}$) denotes the unexpected return of stock i from the previous day's close at 15:00 to 10:00 of the day (from 14:30 to 15:00). In this analysis of inter-day predictability, we include the overnight price changes in estimating the unexpected return for the next day. This is because part of the overnight information is already reflected in the opening price of the next day through the opening auction. Beyond the half-hour interval, we also extend the next day return to both the whole morning session and the whole trading day, to investigate the predictive ability for a longer horizon.[7]

The left part of Table 4 reports the unexpected return predictability for the whole sample. The upper panel shows that the intraday predictability of the first half-hour to the last half-hour is not statistically significant at conventional levels, regardless of the positive slope of 0.5 and R^2 of 1.33%. However, the lower panel shows that the unexpected return predictability from the last half-hour interval to the next day is significant, implying the predictability of informed trading given the way informed contrarian trades are constructed.

Table 4

Unexpected return predictability

All intervals			Intervals with large trades		
	Predictor: $\varepsilon_{i,9:30-10:00}$			Predictor: $\varepsilon_{i,9:30-10:00}$	
	β_1	$R^2(\%)$		β_1	$R^2(\%)$
$\varepsilon_{i,14:30-15:00}$	0.50 (1.13)	1.33	$\varepsilon_{i,14:30-15:00}$	0.76** (2.41)	2.07
	Predictor: $\varepsilon_{i,14:30-15:00}$			Predictor: $\varepsilon_{i,14:30-15:00}$	
	β_2	$R^2(\%)$		β_2	$R^2(\%)$
$\varepsilon_{i,15:00-10:00(+1)}$	0.067*** (2.61)	3.10	$\varepsilon_{i,15:00-10:00(+1)}$	0.094*** (4.08)	3.48
$\varepsilon_{i,15:00-11:30(+1)}$	0.05** (2.26)	1.93	$\varepsilon_{i,15:00-11:30(+1)}$	0.105*** (2.87)	1.91
$\varepsilon_{i,15:00-15:00(+1)}$	0.031* (1.86)	1.54	$\varepsilon_{i,15:00-15:00(+1)}$	0.057* (1.89)	1.74

Note: This table reports the predictive regression results of the unexpected return from market open to market close using Equation (8) as well as from market close to the next day using Equation (9). The evidence for all intervals in the whole sample and for the predictor intervals with large trades are displayed in the left part and right part respectively. All the results were obtained from the regressions of individual stocks first, and then averaged across stocks. The averages of the Newey and West (1987) robust *t*-statistics are shown in the parentheses, and significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively.

[7] For longer horizons of half day and whole day, the predictive regression of Equation (9) similarly can be rewritten as $\varepsilon_{i,15:00-11:30(+1),} = \alpha_3 + \beta_3\varepsilon_{i,14:30-15:00} + \epsilon_{i,15:00-11:30(+1)}$ and $\varepsilon_{i,15:00-15:00(+1),} = \alpha_4 + \beta_4\varepsilon_{i,14:30-15:00} + \epsilon_{i,15:00-15:00(+1)}$ respectively.

As discussed earlier, in intervals with large trades, high information content is embodied in the unexpected returns given the significant price impact of large trades. A positive (negative) information shock causes positive (negative) unexpected returns. Therefore, we are particularly interested in the predictive ability of the unexpected returns of the intervals with large trades. The results, reported in the right part of Table 4, demonstrates both economically and statistically significant predictability, despite the smaller sample size. It is noteworthy that the intraday predictability, shown in the upper panel, turns highly significant when focusing on the intervals with large trades. Both R^2 and the t-statistic increase remarkably compared with that for the results from all intervals. This indicates that the opening sessions with large trades are more likely to have information retained until market close. Specifically, nearly 80% of information revealed in the early morning persists at the market close, as suggested by the slope of 0.76, whereas the lower panel indicates significant predictability of the last half-hour to the next day, although with lower slope values. As the predicted variable expands from the first half-hour to the next morning session and to the whole next day, both R^2 and the t-statistic monotonically decrease. This may be partly due to the diluting effects from new information inflows during the day.

In summary, there is strong evidence that the late afternoon unexpected returns predict that of the next day. Intraday predictability from morning to market close is also present but only significant in intervals with large trades. This suggests strong predictability of informed trading in large size from early morning to market close and from late afternoon to the next day. Together, this evidence provides insightful explanations for the U-shaped informed trading pattern, especially the right-side peak, which is associated with both information retained from the morning and private information that is supposed to arrive the next day.

7 Robustness Tests

In this section, we perform two robustness tests. First, we conduct an autocorrelation test to determine whether there are reversals in price changes caused by informed and uninformed trades captured by our models. Then, we perform an information advantage test, which examines whether informed trades captured by our models have an information advantage, compared with subsequent trades. Both tests indicate that the *VDPIN-PI* model with the modification for price impact can identify informed trades more effectively than the baseline model.

7.1 Autocorrelation Test

We first employ the autocorrelation regression test proposed by Avramov et al. (2006), which is based on Campbell et al.'s (1993) model (CGW). The CGW model suggests that price decreases should result from either negative news or liquidity-driven selling. Uninformed liquidity-driven selling can lead to temporary price decreases, which should subsequently be reversed after the release of selling pressure, whereas informed selling should cause permanent price changes. Avramov et al. (2006) perform an autocorrelation test for the next day for their daily data. To accommodate our five-minute high-frequency data, we consider up to 30 minutes to document the process of return reversals for uninformed trades. The regression is presented in Equation (10) as follows:

$$\varepsilon_{i,j+n} = \phi_i + \left\{\delta_{i,0} Vol_{i,j} + \delta_{i,1}\frac{VS_{i,j}}{VT_{i,j}}(informed) + \delta_{i,2}\frac{VS_{i,j}}{VT_{i,j}}(uninformed)\right\}\varepsilon_{i,j} + u_{i,j+n} \quad (10)$$

where $\varepsilon_{i,j+n}$ is the unexpected return for stock i at the interval from j to $j+n$. Given that we use five-minute returns, $\varepsilon_{i,j+6}$, for example, is the unexpected return for the 30-minute interval from j to $j+6$. $Vol_{i,j}$ is the volume of stock i in interval j to control for the volume effect on return reversal. $VS_{i,j}$ / $VT_{i,j}$ (*informed*) represents the informed sell and $VS_{i,j}$ / $VT_{i,j}$(*uninformed*) represents the uninformed sell of stock i at interval j. If our model is able to identify informed trades, we would expect to find that δ_1 insignificant and δ_2 is significantly negative, as suggested by CGW and Avramov et al. (2006). Given that we found the price impact from large trades and proposed the subsequent modification to intervals with large trades, it is more meaningful to report and analyse the findings between the baseline and modified measures for these intervals in particular.[8]

Table 5 presents the results of the autocorrelation test for intervals with large trades for the baseline and modified models. δ_2 is significantly negative for the modified model, which indicates that the return reversal is indeed observed for the uninformed trades measured by the modified model, consistent with the CGW theory. Meanwhile, the large informed trades captured by the modified measure since they do not show subsequent price reversals (δ_1 are all positive) are unlikely to be executed by liquidity traders. However, a positive δ_2 is observed for the baseline model, thereby, implying that uninformed trading is not properly measured. The results suggest that the modified measure is able to distinguish large informed trades

[8] The results for the whole sample are available upon request.

from large liquidity trades.[9]

Table 5
Autocorrelation test for intervals with large trades

	Baseline *VDPIN*				*VDPIN-PI*			
	$\delta_0 * 10^5$	δ_1	δ_2	R^2(%)	$\delta_0 * 10^5$	δ_1	δ_2	R^2(%)
$j+1$	-1.71*	-0.31	0.69	0.89	-3.81***	0.54**	-0.76**	2.86
	(-1.73)	(-1.29)	(1.41)		(-3.69)	(2.19)	(-1.97)	
$j+2$	-1.98*	-0.34	0.59	1.25	-3.65***	0.59***	-0.68***	2.70
	(-1.86)	(-1.23)	(1.32)		(-3.73)	(3.88)	(-3.36)	
$j+3$	-2.87*	-0.40	0.53	0.82	-3.93***	0.80***	-0.73***	1.59
	(-1.85)	(-1.10)	(1.58)		(-4.02)	(4.64)	(-3.53)	
$j+4$	-2.62*	-0.19	0.35	0.52	-3.20***	0.61***	-0.51***	1.20
	(-1.79)	(-0.98)	(1.40)		(-3.69)	(3.83)	(-3.91)	
$j+5$	-2.30	-0.11	0.15	0.23	-2.81***	0.25*	-0.34***	0.73
	(-1.61)	(-1.06)	(1.10)		(-2.77)	(1.85)	(-2.72)	
$j+6$	-2.11	-0.08	0.09	0.07	-2.10**	0.17	-0.34	0.04
	(-1.58)	(-0.93)	(0.85)		(-2.41)	(1.12)	(-1.04)	

Note: This table summarises the results of the autocorrelation test as in Equation (10). The test was undertaken for five-, 10-, 15-, 20-, 25- and 30-minute intervals. All the results were achieved from regressions of individual stocks first, and then averaged across stocks. The averages of the Newey and West (1987) robust *t*-statistics are shown in the parentheses, and significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively.

7.2 Information Advantage Test

An informed trading measure can either overestimate or underestimate the probability of informed trading. For instance, liquidity trades, given their portfolio or inventory motives for trade, can be mistakenly captured by our measure. The robustness of an informed trading measure could be tested by examining the extent to which the trades captured in this measure have an information advantage over followers. We examine whether the proportion of the trades captured in the baseline *VDPIN* (and *VDPIN-PI*) can indeed trade at a better price than the subsequent price that has fully reflected the relevant information. The results of the autocorrelation tests imply that, in China's stock market, it takes about 30 minutes for stock prices to fully impound new information. Hence, we postulate that a buy (sell) trade has information advantage if traders can buy (sell) at a price that is lower (higher) than the price of 30 minutes later.

[9] We find large trades have the highest percentage of informed trades among all trade size categories. However, one concern is that some of the large trades are probably executed by liquidity traders, such as some financial institutions (Admati and Pfleiderer, 1988), and these large liquidity trades could be mistakenly measured as large informed trades. Unlike developed markets, China's stock market is dominated by individual traders. Over 70% of investors are actually retail investors. Financial institutions, such as pension funds, were not allowed to invest in the stock market until April 2017. Therefore, large trades in China's stock market are less likely to be executed by institutions for liquidity reasons.

As a benchmark, we first examine the proportion of all trades that have information advantage using Equation (11). The informed trades captured by the baseline *VDPIN*and *VDPIN-PI* can be tested for information advantage through Equation (12) and (13) as follows:

$$PT_{i,j}^{IA} = \frac{VB_{i,j}}{VT_{i,j}}(P_t < P_{t+6}) + \frac{VS_{i,j}}{VT_{i,j}}(P_t \geq P_{t+6}) \tag{11}$$

$$VDPIN_{Base_{i,j}}^{IA} = \frac{VB_{i,j}(\varepsilon_{i,j} < 0, P_t < P_{t+6})}{VB_{i,j}(\varepsilon_{i,j} < 0)} + \frac{VS_{i,j}(\varepsilon_{i,j} \geq 0, P_t \geq P_{t+6})}{VS_{i,j}(\varepsilon_{i,j} \geq 0)} \tag{12}$$

$$\begin{aligned} VDPIN - PI_{i,j}^{IA} = & \left[\frac{VB_{i,j}(\varepsilon_{i,j} < 0, P_t < P_{t+6})}{VB_{i,j}(\varepsilon_{i,j} < 0)} + \frac{VS_{i,j}(\varepsilon_{i,j} \geq 0, P_t \geq P_{t+6})}{VS_{i,j}(\varepsilon_{i,j} \geq 0)}\right](②③⑤) \\ & + \left[\frac{VB_{i,j}(\varepsilon_{i,j} \geq 0, P_t < P_{t+6})}{VB_{i,j}(\varepsilon_{i,j} \geq 0)} + \frac{VS_{i,j}(\varepsilon_{i,j} < 0, P_t \geq P_{t+6})}{VS_{i,j}(\varepsilon_{i,j} < 0)}\right](①④) \end{aligned} \tag{13}$$

where P_t and P_{t+6} represent the transaction prices at time t and time $t + 6$ (30 minutes later), respectively, which are used to indicate whether a trade is embedded with information advantage. $PT_{i,j}^{IA}$ represents the proportion of all trades that have information advantage for each stock and at each interval. $VDPIN_{Base_{i,j}}^{IA}$ ($VDPIN - PI_{i,j}^{IA}$) represents the proportion of trades captured by $VDPIN_{Base_{i,j}}$ ($VDPIN - PI_{i,j}$) that have information advantage, because the traders can buy (sell) at a price that is lower (higher) than the price of 30 minutes later. The intraday proportion of trades that have information advantage is presented in Figure 6 for all trades as well as informed trades captured by the baseline and modified models.

Figure 6 clearly shows that, compared with all trades and trades captured by the baseline *VDPIN* with much higher probability, the trades captured by the *VDPIN-PI* indeed have information advantage throughout the trading day. This result strongly suggests that *VDPIN-PI* is a more efficient proxy of informed trades than the baseline *VDPIN*.

Figure 6. Intraday pattern of proportion of trades with information advantage

Note: The line for 'All Trades' represents the proportion of all trades that have information advantage ($PT_{i,j}^{IA}$ in Equation (11)). The line for 'Baseline *VDPIN* Trades' represents the proportion of trades captured by the baseline *VDPIN* that have information advantage ($VDPIN_{Base_{i,j}}^{IA}$ in Equation (12)). The line for '*VDPIN-PI* Trades' represents the proportion of trades captured by *VDPIN-PI* that have information advantage ($VDPIN - PI_{i,j}^{IA}$ in Equation (13)). All results are obtained first from computation of individual stocks, and then averaged across stocks.

To further test the profitability of informed trading captured by our model, we directly test whether they can make profit across different time periods.

Table 6:
Accumulated Returns of Informed Tradings Measured By VDPIN and VDPIN-PI

	VDPIN			VDPIN-PI		
	Large	Medium	Small	Large	Medium	Small
30 Minutes	2.34%	1.21%	0.08%	2.65%	1.24%	0.05%
1 Hour	1.84%	0.76%	0.04%	2.27%	0.99%	0.02%
1Day	1.79%	0.31%	0.07%	2.06%	0.75%	0.06%
1Week	1.15%	0.42%	0.03%	1.50%	0.53%	0.02%
1Month	1.23%	0.55%	0.01%	1.31%	0.68%	0.00%
3 Months	1.10%	0.33%	0.00%	1.24%	0.39%	0.00%

Note: This table shows the results of the Accumulated Returns of Informed trades Measured by VDPIN and VDPIN-PI for large, medium and small sizes for the period of 30 minutes, 1hour, 1day, 1week, 1month and 3 months.

From Table 6, we can see large sized informed trades make more positive profits than medium sized informed trades from both VDPIN and VDPIN-PI in almost all periods in the zero sum stock market. And return of small sized informed trades are equal to zero. Moreover, large sized informed trades from VDPIN-PI have high profit than ones from VDPIN. These are additional evidence to prove the informed trades we capture is indeed informed. And the VDPIN-PI have better power in detecting informed trades.

8 Conclusion

Contrarian trades have been proposed and applied by many studies to represent informed trades. The notion is that, considering the rationality of investors - especially those with private information - informed subjects frequently act as contrarians (Drehmann et al. (2005)). However, a large trade price impact poses a challenge to the proxy of informed trades by contrarian trades. This issue is linked to another strand of research on the camouflage behaviour of informed traders, which means they may split large trades into medium sizes to mitigate the price impact cost. Hence, an examination of trade size variations is essential to understand informed trades. This article conducts, at the transaction level, an investigation of informed trades on the CSI300 component stocks in China's market. We begin by applying the baseline measure (*VDPIN*), which uses contrarian trades to proxy for informed trades. Further examination of the informed trades in three trade size categories and price impact analyses lead us to incorporate price impact into the modified model, that is, *VDPIN-PI*. We also conduct a predictability test to seek causes that explain the detected intraday pattern of informed trading.

Our main findings are as follows: (i) We identify the aggregate intraday U-shaped informed trades for CSI300 constituent stocks, similar to the findings from other markets. (ii) On examining different trade size categories, we find that informed trades are heterogeneous in both levels and variations within the day, and midsized trades show the most similarity to the overall pattern. (iii) As revealed by a trade composition analysis, the aggregate U-shape of informed trades is essentially driven by the change of trade size composition within the day. (iv) Large-sized trades exert a substantial price impact that affects the detection of informed trades using the contrarian trades. By accounting for price impact, the modified model (*VDPIN-PI*) can capture informed trades more effectively, as confirmed by the robustness tests. (v) The results from the robustness tests also suggest that the market takes about 30 minutes to digest information. (vi) The results from the predictability analysis, especially of the intervals with large-sized trades, imply that the informed trading at market close is driven not only by information retained from early morning (late-informed trading) but also by private information supposed to arrive the next day. This finding provides new insights for the high informed trading found at market close.

In summary, the results are generally consistent with those of Admati and Pfleiderer (1988) regarding intraday patterns of volume and price variability, which suggests that informed (and liquidity) trading should concentrate at the open and close at the aggregate level. Further, this study incorporates the unexplored dimensions of trade size composition and predictability into the empirical investigation of the aggregate U-shape pattern of informed trading. The findings stated in (iii) and (vi), in addition to the time-of-day effect, explain the intraday U-shaped informed trading. Moreover, given the non-negligible nature of price impact, this study reveals the importance of incorporating price impact in informed trading modelling.

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Chapter 3

Informed Tradings Prior to Earnings and M&A Announcements in China Stock Market

Abstract

This chapter focuses on the study of informed trading around earnings and M&A announcements in China stock market. By adopting both indirect and direct measures, it is found that informed tradings are more pronounced before earnings announcements than before M&A announcements. We further investigate the relation between firm characteristics (size and profitability) and the level of informed tradings. Results show that smaller companies have more informed trading before both earnings announcements and M&A announcements. Companies of both high and low profitability have more informed trading compared with companies of medium profitability before earnings announcements. Nevertheless, only companies with poor financial performances have higher levels of informed trading before M&A announcements. Moreover, companies with higher level of informed trading seem to have less or even negative long term benefits from M&As on both stock price and financial performance. We argue this could because the initial motivation of mangers to launch M&A transactions is the gains from insider tradings instead of the long term interests of the companies. We argue that informed tradings prior to M&A announcements in small and non-profitable firms are more likely to be executed actual insiders as a result of agency problem and weak market regulation in China.

1 Introduction

Insider trading is regarded as illegal activities in almost every country, whereas insiders still kept trying to benefit from superior information. This is already well documented in past literature in developed financial markets. China stock market is generally considered to be a large but less developed and weak regulated emerging market where insider trading should occur at a higher frequency. Regulators in China have shown great attention in detecting and reducing insider trading in the recent year. However, it is still a pending problem for researchers to detect insider tradings because of two reasons. First, there is always a confounding relationship between the concept of informed trading and insider trading. Informed trading comprises of insider informed trading and non-insider informed trading. Second, without the data which reveals the identity of traders information, it is difficult distinguish whether a trade is based on publicly available information or based on superior private information (Ordu & Schweizer, 2015). We suggest that a possible way of seeking indirect evidences of insider informed trading is to capture abnormal trading behaviors prior to the event of a significant information resale, for example, the event of firm announcement. There are two types important firm announcements, the scheduled earnings announcements and the unscheduled merger and acquisition (M&A) announcements. Clear evidences of informed tradings around earnings announcements are found in literature (Le et al., 2019). Nevertheless, fewer literature works on the informed tradings around Merger and acquisition transactions. Aktas (2007) provides the closest work with this study. Since M&As are one of the most important company-specific events, the stock price movements after the M&A announcements depends on market understanding about the value of the M&As in developed market. However, it is extremely common in China stock market that share prices of the acquiring companies will have a dramatic increase regardless of whether the transaction is beneficial or not. This creates opportunities to obtain huge abnormal gains for anyone who has access to insider information of the M&As. Exploring the reason of this phenomenon, investigating the trader's behavior and firm characteristics could provide insights for investors, companies and also regulators.

This study not only aims to find evidences for the existence of informed trading, but also tries to explore possible company characteristics which may lead to different levels of informed trading. Similar to the work of Mohil (2018), it is not our purpose to distinguish between insider informed trading and non-insider informed trading, but to investigate the information leakage and its influences ahead of announcements. The informed trading around earnings announcements is also examined for comparison. Inspired by the statistics of officially reported insider trading cases during M&A periods (see in Section 2.1) by the China Securities Regulatory Commission, we conjecture that size and financial performance could be two key firm characteristics which may be linked to the levels of informed tradings. The fundamental logic of this conjecture is that mangers may concern more about their individual gains from insider tradings rather than the real interests of the company as a result of the compensation effect (Shleifer & Vishny,1988). Furthermore, companies with smaller market capitalization are believed to have higher information risk (Barry & Brown, 1984) and would be easier to be manipulated on the stock price for higher insider trading gains. Similarly, companies with poorer financial performances give mangers more sufficient motivations to launch M&As as a result of agency problem and reflection effect (Kahneman, 1979). Based on this, it is also reasonable to speculate that smaller companies with poorer financial performances are more likely to be engaged with insider tradings. On the other side, if mangers have to trade-off between personal gains from insider tradings and the long term interests of companies when launching M&A transactions, the shareholders should be be more careful whether M&A transactions can truly help companies on the fundamental side.

The data used in this chapter includes 300 stocks with 1000 earnings announcements and 161 stocks with 210 M&A announcements (see in Section 3). Following the work of Park et al. (2014) and Le et al. (2019), we firstly employ indirect measures of informed trading including level of information asymmetry, cumulative abnormal returns, abnormal turnover and trade imbalance around both earnings and M&A announcements (see in Section 4.1). To test the efficiency of these indirect evidences, we further investigate the predictability of post-announcement abnormal return by pre-announcement tradings (see in Section 4.2). Since evidence from direct informed trading measures should be more persuasive in verifying our conjecture, the unconditional probability of information-based trading (PIN) by Easley et al. (1996) and the Volume Weighted Dynamic Probability of Informed Trading of Price Impact (VDPIN-PI) developed in Chapter 2 are implemented (see in Section 4.3). Finally, in order to study the relationship between firm characteristics (size and profitability) and the level of informed tradings, we employ OLS regression proposed by Aslan (2011) (see in Section 4.4).

We find that informed tradings are more pronounced before earnings announcements than before M&A announcements. [1] We argue that this is because M&A announcements contain more private information. Investors with private information will try to camouflage by minimize the volume of each trading for less price impact (Barclay and Warner, 1993). This makes them more difficult to be detected. The second find is that smaller companies have more informed trading before both earn-

[1] To be precise, although we suggest some of the informed trading activities that we capture in this study are very likely from actual insiders with private and superior information during M&A events, it is also possible that these trades could from anticipators like specialists or large institutional investors who can judge based on public information or even trace the signal of insiders before the formal announcements. Therefore, we choose to the use a wider concept, informed trading, when analyzing results and presenting findings in the following of the study.

ings announcements and M&A announcements. We argue that this is because smaller companies have higher information asymmetric. Moreover, we also find companies of either high or low profitability have more informed trading compared with companies of medium profitability before earnings announcements. The reason could be the fundamental information of earnings announcements is indeed the profitability of firms. Investors choose to trade on firm with either outstandingly good or bad companies.

Finally, only companies with poor financial performances have higher levels of informed trading before M&A announcements. These companies seem to have less or even negative long term benefits from M&As on both stock price and financial performance. We suggest that informed tradings and prior to M&A announcements in small and non-profitable firms are very likely to be executed by actual insiders as a result of agency problem. The initial motivation of mangers to launch M&A transactions could be the gains from insider tradings instead of the long term interests of the companies. The incomplete market environment (e.g., distempered mechanism of IPO and delisting, irrational investors, lack of short selling opportunities) has provided very low cost of making illegal or unethical management decisions. Two robustness tests also produce supportive outcomes to our main results in this study.

Different from the regulators who care more about detecting insider tradings, we believe that it is more meaningful to study the firm characteristics which leads to higher informed trading level and to ask whether M&A can actually help companies in long terms. The results of this research could be indicators for both investors and regulators when assessing the impact of M&A activities. Based on the rationales behind our findings, we propose that retailed investors in China stock markets should study more about the synergy of M&As instead of simply treating all M&As as good news. On the other hand, supervisions after M&As such as the completeness of valuation adjustment mechanism could be efficient and powerful regulation means.

2 Literature Review and Hypotheses

2.1 Background: Unique Situation in China Stock Market

China, the second largest economic entity in the world, is generally considered as having a less developed financial market which more the 70% of trading volumes are contributed by retail investors. With investors of low professional competence and poor regulation power, the stock market of China has somehow become a fertile ground of insider trading. Insiders take benefits at the cost of others paying extremely low financial and illegality cost until Xu Xiang, the CEO of Zexi fund was put into prison in September 2015 for insider trading and market manipulation. 23 listed companies were involved. The stock-based funds under his management have been ranked in the first place among more than 1600 competitors for 18 months with a net return of

3000% in five years. Since then, the CSRC (China Securities Regulatory Commission) announced that it is essential to take actions to control illegal activities in the stock market. However, the numbers of disclosing insider trading still kept increasing. As the CSRC reported, there are 418 officially announced and punished insider trading events during 2015 to 2018. 75.84% among these cases are related with M&A transactions. And 21.33% are also confirmed with market manipulation. Reports from CSIPF (China Securities Investor Protection Fund Corporation) suggest that insiders do not simply trade on information. They try to manipulate information and stock price during M&A transactions in China. Why are M&A transactions are highly correlated with informed trading and insider trading in China? Four unique factors are considered to be the inducements of this phenomenon in China stock market:

Lack of listing opportunities and delisting mechanism

As a result of imperfect delisting mechanism, there are only 60 stocks delisted in China for 18 years from 2001 to 2018. Moreover, no stock is delisted from 2009 to 2012. At the same time, the waiting queue of IPO companies has been more than 900 since 2012, with an average waiting period of 3.6 years. Therefore, listed stocks become quite scarce resources and could create huge benefit in China (Lee, 2015, 2018). Stocks with poor financial performance or even under distress are still hot because of the value of their "shells". This makes stock with poor financial performance still have strong ability to complete significant M&A transactions. However, it is highly suspicious that M&A transactions can truly help stocks with poor financial performance on the fundamental side as a result of agency problem and reflection effect in China.

Irrational beliefs of retail investors about M&A transactions

In a market where more than 70% of the trading volume is contributed by retail investors, herding effect and irrational judgments occur in great prevalence. The judgments of retail investors can be easily misled by exaggerated publicity and false gossip. Among the 5760 M&A transactions from 2014 to 2017 in China stock markets, 95.56% show increase in the stock price on the first announcement day. Irrational beliefs about M&A transactions is deep-rooted in the mind of retail investors. This provides a perfect environment for insiders to benefit from M&A transactions in the secondary market. The pursuit of retail investors could lower the cost of information and price manipulation. The high liquidity provided by retail investors also help insiders sell their inventories and realizing profit.

Limited way to short selling

It is different from developed markets where investors are able to short the stocks if they believe the M&A is harmful to the company. Investors in China stock market are almost impossible to make profits on bad news by short selling. This provides huge advantage for insiders to collude with managers and release good news. At the same time, other investors also cannot short the stock even they have negative options on the announcement.

Extremely low illegality cost for insider trading and market manipulation

China stock market is regarded as having poor supervision ability and regulatory power. The Securities Act of China only includes a maximum penalty of 600,000RMB for any illegal activities until 2020. There is no single criminal liability case until Xu Xiang was put into prison. Compared with the integral legislative system and investors protecting policies in development, China exhibits extremely low illegality cost for insider trading and market manipulation.

2.2 Literature Review

2.2.1 Insider trading and informed trading

Insider trading is defined as a kind of malpractice where in trade of a company's securities is undertaken by people who can access to the otherwise nonpublic information which can be crucial for making investment decisions. When insiders, e.g., key employees or executives who have opportunities to access the strategic information about the company, use information superiority to trade in the company's stocks or securities, it is called insider trading and is highly discouraged by the regulators to promote fair trading in the market for the benefit of the common investor. The definition of informed trading is more complex and less specific. Anyone with more advanced information or having better ability of evaluating information can be classified as an informed trader. Since it is difficult to obtain the trading data which is from actual insider traders, most methodologies like PIN (Easley et al., 1996) and DPIN (Avramov, 2006) aim on detecting informed trading. This research also applies methodologies used to test the existence of informed trading. However, it is reasonable to claim that the informed traders which are detected during a short window right before the M&A announcements are very likely to be insiders.

2.2.2 Informed trading measures

Informed trading (trading based on insider/private information) prior to public announcement of important firm events (such as earnings announcements, announcements of M&As) is well documented in the literature. Since informed trading is not directly observable, several market indicators can be used to assess whether there is evidence of information leakage onto the market prior to public announcements of these events. The market indicators of information leakage used in the literature include increased cumulative abnormal volumes (Ajinkaya and Jain, 1989), widen bid-ask spread (McInish and Wood, 1992; Aktas et al. 2007), order imbalance (Easley et al. 1996), and increased permanent price impact of trades (Glosten and Harris, 1988; Hasbrouck, 1991a/b). There are also other models and measures developed to capture informed trading. For example, Easley and O'hara (1996, 1997) develop a structural market microstructure model to measure the probability of information-based trading (PIN), based on observable data on the number of buys and sells from the trading process. Avramov et al. (2006), Chang et al. (2014) and Chang and Wang (2019) suggest that contrarian trades (according to the direction of unexpected returns) are akin to informed trades. If there is evidence of information leakage prior to public announcement of important firm events and the pre-announcement informed trading as captured by the above measures is greater than the one estimated over the benchmark period, the existence of informed trading is confirmed of the abilities of those informed trading measures to capture informed trades are proved. However, there is concern whether those informed trading measures widely used in the literature truly capture informed trading. For example, Aktas et al. (2007) investigate informed trading around a sample of merger and acquisition announcements that took place on Euronext Paris between 1995 and 2000. They find that while there is clear evidence of information leakages during the pre-event period as indicated by increased cumulative abnormal volume, bid-ask spread, and the permanent price impact of trade, the behavior of Easley et al.'s (1996, 1997) PIN seems to be in contradiction with the evidence. They argue that the surprising behavior of the PIN is due to two defects of the measure: (1) it only reflects the number of orders, while the volume is more relevant; (2) it captures the effect of public information as well as private information. Duarte and Young (2009) indicate that the PIN of Easley et al. (1996, 1997) can actually be decomposed into two components and that only one component (adjusted PIN) measures asymmetric information whereas the other (probability of symmetric order flow shock) measures illiquidity effects unrelated to information asymmetry. Kenneth (2020) exploits hand-collected data on illegal insider trades to provide new evidence on the ability of a host of standard measures of illiquidity to detect informed trading, finding that when information is short-lived, only absolute order imbalance and effective spread are statistically and economically robust predictors of illegal insider trading. However, when information is long-lasting, insiders strategically time their trades to avoid illiquidity, and none of the standard measures including bid-ask spreads, order imbalance, Kyle's l, and Amihud illiquidity are reliable measures informed trades.

2.2.3 Informed trading and Earnings and M&A announcements

Earnings announcements, as vital public information events, help the market informed and remove information asymmetry between the company and investors. As a proxy of measuring informed trading, information asymmetry is discussed that may be increased around announcements. For example, it is proved that quoted depths decrease, bid-ask spreads and the adverse selection component of spreads increase prior to earnings announcements (Lee et al., 1993; Krinsky and Lee, 1996). Chae (2005) reports that the cumulative trading volume decreases around earnings announcements, and he finds that the decrease in trading volume is positively related to information asymmetry. Ajinkaya and Jain (1989) point out that recognition of autocorrelation in daily trading volume is advantageous for detecting abnormal trading. Park et al. (2014) investigate that whether informed traders trade profitably around the earnings announcements on the basis of assuming institutional investors are informed investors. They find that informed traders exploit superior information to make profits or avoid loss specially around earnings shock announcements.

Informed trading around M&A has also been one of the main topics in finance and accounting literature over a long period of time. Easley et al. (2002) use a market microstructure model to prove that PIN and firm size, which is one of the important characteristics of a firm, are strongly negatively correlated. Aslan et al. (2011) investigate what types of firms have high information risk by determining the relationship between a firm's PIN as estimated from trade data and firm characteristics as analyzed from accounting data. Aktas et al. (2007) investigate informed trading around several samples of M&A announcements that happened on Euronext Paris. They find the presence of informed traders by analyzing cumulative abnormal volumes, while they prove that a decrease in the probability of informed trading (PIN) before M&As and an increase after the information release. Chung et al. (2005) prove that the price impact of trades and are positively and significantly related to the probability of information-based trading. Kryzanowski and Tran (2017) prove that information that information leakage prior to M&A announcements is influenced by firms' characteristics. They believe that PIN reflects the related activities of insiders and other informed traders about takeover intention.

2.2.4 Insider trading and Corporate Governance

Bhattacharya (2002) finds that companies whose stock prices are manipulated show abnormal behavior corporate governance, such as the features of the board of directors and shareholding structure, etc. He suggests that insider trading lower the efficiency of Corporate Governance (Glosten, 1989). Tang (2013) find poor corporate governance system interacts with abnormal insider trading and abnormal accruals, thereby aggravating insider expropriation on outside investors. Wang (2010) finds that the corporations with asymmetric information, family business, low institutional stock holdings and no payment for directors, due to agency problem and poor monitoring system, are more likely to have illegal insider trading. As a result, insider trading tends to discourage corporate investment and reduce the efficiency of corporate behavior. At the same time, managers could also be more willing to take risky investments and create significant news like M&As in order to gain higher profit through insider trading. Moreover, the low efficiency in corporate governance leads to an increase in cost of capital. Shi and Jiang (2004) use the methodology of PPD (Potential Probability Disgorgement) to test the influences of insider trading on the volatility and information asymmetry of stocks in China. Results show that insider trading increases the stock price, volatility as well as information asymmetry and good disclosure could help reduce information asymmetry.

Past literature discusses corporate governance and agency problem in the situation that insiders trying to make profits on private information that the M&A transaction which actually beneficial for the company (Noe, 1997). However, the situation in China could be more egregious. Roulstone (2003) shows that paying CEOs with higher compensation is one direct way for firms to restrict insider trading. For companies with financial performance which are not able to pay high compensation, managers could enforce the company into a M&A transaction which would harm the company for their own interests. The reflection effect of the prospect theory is developed by Kahneman and Tversky (1979), and it suggests that people tend to be risk averse when face possible gains, but tend to be risk seeking when facing possible losses. Barry & Brown (1984) point out that companies with smaller sizes show higher information risk. Therefore, when facing highly possible distress, companies with poor financial performance could be willing to do high risky M&As for the following reasons. As a result of the unique environment in China as discussed, it is very likely that the M&A news will boost the stock price. The crisis of company could be temporary respited. Mangers could obtain huge benefits from the inside information in the secondary market at the loses of outsiders.If the risky M&A turns out to be beneficial, mangers would win praise and awards for the decision. If it turns out to be harmful, the company simply can not be any worse. In Summary, insider trading and price manipulation are more likely to happen in companies with poor financial performance.

2.3 Hypotheses Development

Chae (2005) investigates trading volume before scheduled versus unscheduled corporate announcements to explore how the timing characteristic of corporate announcements affect traders' response to increased information asymmetry around the announcements. Specifically, in response to scheduled and hence predictable firm announcements (e.g. earnings announcements), discretionary liquidity traders will postpone trading until the announcement is made and the information asymmetry is resolved to minimize adverse selection costs related to the information release. Therefore, liquidity trading volume decreases prior to scheduled announcements. On the other hand, when timing information of unscheduled announcements (e.g. M&A announcements, bond rating announcements) is not available, discretionary liquidity traders will not change the timing of their trades. Hence liquidity trading volume will not decrease prior to unscheduled announcements. Barclay and warner (1993) argue that investors with private information prefer to trade when market liquidity is high in order to minimize the price impact of their informed trades and to camouflage their identities. Combining the views and findings of Barclay and Warner (1993) and Chae (2005), we conjecture that knowing that discretionary liquidity traders are likely to postpone their trades until after the scheduled announcements, informed traders tend to follow suit and be less active prior to scheduled announcements. Deliberately postponing trades by discretionary liquidity traders as well as by informed traders are less likely to occur for unscheduled announcements. Therefore, our first hypothesis is as below:

H1: The levels of informed trading prior to scheduled earnings announcements are less pronounced than that prior to unscheduled M&A announcements.

Atiase (1985) provides empirical evidence that firm size is positively related to the amount of pre-disclosure information dissemination, that is, smaller firms have lower level of pre-disclosure information disseminated, and hence have higher level of information asymmetry. Chae (2005) documents that prior to earnings announcements, the cumulative trading volume decreases, and his interpretation of the results is that the decreasing trading volume is associated with increased information asymmetry. Specifically, Chae (2005) finds that a decrease in trading volume prior to earnings announcement is more prominent for small firms and firms with less analyst following, implying that small firms show higher level of information asymmetry than that of larger firms. Several studies document the positive relation between analyst following and market liquidity (Brennan and Subrahmanyam, 1995; Roulstone, 2003). The findings of those studies imply that analysts reduce information asymmetry by providing information to the public. This line of research also suggests that small firms have higher information asymmetry, because large firms normally have higher analyst coverage than small firms. Following the literature, Park et al. (2014) directly use firm size (as well as three other variables, including analyst following, idiosyncratic risk and Amihud's illiquidity ratio) as the proxy for information asymmetry. We hence propose the second hypothesis:

H2: The levels of informed trading prior to corporate announcements (e.g. earnings and M&A announcements) are higher for small firms than for large firms.

There is considerable evidence that average returns to acquiring companies from making acquisitions are at best slightly positive, and in most cases significantly negative, as opposed to the generally positive returns to target companies (Bradley, et al. 1988; Roll, 1986). There are two classes of explanations for the widely documented negative bidder returns. Some suggest that negative bidder returns are purely a result of stock financing of acquisitions that reveals adverse information about acquiring firms, that is, overvalued stocks against poor financial performance (Asquith, et al., 1987). The release of such adverse information would lead to selling pressure and hence negative returns to the acquiring firms. It also implies that there is no such selling pressure on good financial performance firms. An alternative explanation on the negative bidder returns is made by Morck, et al. (1990), who suggest that poor financial performance drives managers to try something new, or bad managers have more incentive to acquire to assure the survival of the firm. The negative bidder returns reflect the penalties of the market to bad acquisitions made by managers with private objectives or incentives. The above two explanations on negative bidder returns both suggest that more information, in particular, bad information, is associated with acquisition announcements made by poor financial performance firms than by good financial performance firms. Moveover, since investors in China have irrational beliefs of retail investors about M&A transactions in China, this leads to irrational price increase in stock the price when the M&A is announced. This could further influence the initial motivations of mangers to launch M&A transactions. They could prefer the gains from insider tradings rather than the long term interests of the companies. Based on this, it is also reasonable to speculate that smaller companies with poorer financial performances are more likely to be engaged with informed tradings. This leads to our third hypothesis:

H3: The levels of informed trading prior to acquisition announcements are higher for poor financial performance acquiring firms than for good financial performance acquiring firms.

3 Data

The whole dataset consists of two parts. The first part shares the same data used in Chapter 1 and Chapter 2, in which includes high-frequency data of 300 individual stocks CSI300 index from January 2012 to December 2014. We exclude the first 100 stocks which ranked in the front by firm size since most of them are financial companies, real estate companies and large state-own companies. The second part of data consists of 100 stocks which ranked at the last 100 by firm size from CSI Smallcap 500 index. The second part data only includes the time period from October 2013 to September 2014, in order to gain sufficient data around the annual earnings announcements and the earnings announcements of the first quarter which both usually take place in April. The annual earnings announcements are the most important reports to be investigated. The first quarter report is more likely to contain surprisingly information (e.g., reversal of losses).[2]Therefore, there are 300 individual stocks in total for the dataset used in this chapter.

To investigate (H2, H3), we divide the 300 stocks into three groups named as 'large, medium and small ' by the firm size reported in the annual report of 2013 (released in April 2014). Each group contains 100 stocks. There are 2 years with 4 earnings announcements for each stock which have complete available data (because of the misplace of data period and earnings announcements date) in the large and medium sized groups. There is 1 year with 2 earnings announcements for each stock in the small sized group. 1000 earnings announcements could be studied in the dataset in total (see in Table 1). To investigate (H3), we also divide the data into another three groups named as 'high, medium and low ' by the profitability (return on equity) reported in the annual report of they year 2013 (released in April 2014). Furthermore, we search the announcements of M&A (first announcement) of all 300 stocks during our data period. M&A transaction values below 50 million RMB are deleted from the sample. Results show that there are 161 stocks with 210 M&A announcements available. Finally, we also divide them into three groups by firm size and profitability separately. Detailed summaries are in Table 1 as follow:

Table 1: **Descriptive Statistics of Announcement Events**

Panel A : Earnings Announcements								
	Size				Profitability			
	Total	Large	Medium	Small	Total	High	Medium	Low
No. of St	300	100	100	100	300	100	100	100
No. of An	1000	400	400	200	1000	390	386	224
Average	23.02	37.81	21.41	9.85	9.51%	15.67%	9.83%	2.02%
Medium	20.84	33.46	20.34	8.73	11.12%	16.85%	9.55%	-4.12%
Std.Dev	8.26	6.82	7.46	5.10	13.22	18.84	9.03	23.43

Panel B: M&A Announcements								
	Size				Profitability			
	Total	Large	Medium	Small	Total	High	Medium	Low
No. of St	161	53	54	54	161	53	54	54
No. of An	210	58	66	86	210	83	57	70
Average	19.30	31.44	19.05	8.30	7.98%	17.67%	11.82%	-8.02%
Medium	17.68	28.13	17.32	7.99	13.44%	21.13%	12.17%	-13.12%
Std.Dev	9.18	8.32	9.23	7.45	16.73	16.01	13.12	24.17

This table reports the number of firms and numbers of announcements during our data period and the descriptive statistics. Panel A reports 1000 earnings announcements for 300 stocks which divided into three groups by firm size and profitability. Panel A reports 210 M&A announcements for 161 stocks which are also divided into three groups by firm size and profitability.

[2]The regulations of A share stated that companies that fail to make profit in three years continuously should be desisted from the exchange market. Therefore, companies intend to account all losses including long-term losses and unrealized potential losses in the second defective annual report. This makes the earnings announcements of the first quarter being the first signal of loss reversal.

4 Methodology and Empirical Results

Following the work of Park et al. (2014) and Le et al. (2019), we try to seek indirect evidences of informed trading from level of information asymmetry, cumulative abnormal returns, abnormal turnover and trade imbalance around announcements (see Section 4.1). These variables can be considered as instruments for further study. And to test the efficiency of these indirect evidences, we further investigate the predictability of post-announcement abnormal return by pre-announcement tradings (see Section 4.2). Applying direct measures of informed trading is an alternative way to verify our hypotheses. Therefore, the unconditional probability of information-based trading (PIN) by Easley et al. (1996) and the Volume Weighted Dynamic Probability of Informed Trading of Price Impact (VDPIN-PI) developed in Chapter 2 are implemented (see Section 4.3). Finally, in order to find evidences to support the hypothesis 2 and 3, we employ the OLS regression proposed by Aslan (2011) to investigate the relationship between firm characteristics of size, profitability and the level of informed trading (see Section 4.4). The direct measures in Section 4.3 and 4.4 are the key methodologies which show main results which verifying our hypotheses.

4.1 Indirect Evidences of Informed Trading around Announcements

4.1.1 Information Asymmetry Prior to Announcements

Idiosyncratic risk and Amihud's illiquidity ratio are two commonly used measures to test information asymmetry. Following Ferreira and Laux (2007) and Park et al. (2014), we first calculate the stock excess return by Eq. (1) using the daily returns over the two periods, from -51 to -26 and from -25 to -1. Following that, we measure the idiosyncratic risk by Eq. (2). The illiquidity ratio introduced by Amihud (2002) is also employed to investigate the possible price impact of informed trading. Amihud's illiquidity ratio is defined as a ratio of absolute stock returns to trading volume. Using daily stock returns and trading volume to measure Amihud's illiquidity ratio over the two periods, from -50 to -26 and from -25 to -1 by Eq.3 (3)[3]:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + e_{i,t} \tag{1}$$

$$idiosyncratic\, risk = \sigma^2_{i,e} = \sigma^2_i - \frac{\sigma^2_{i,m}}{\sigma^2_m} \tag{2}$$

$$Cumulative\ Amihud = \frac{\sum_{d=1}^{t_1,t_2} \frac{|r_{i,t}|}{Volume_{i,t}}}{D_{i[t_1,t_2]}} * 10^9 \tag{3}$$

[3]We multiply the results of Eq. 3 by 10^9 to for better observation. Similar Actions are also applied in the following result.

where $r_{i,t}$ is the excess return of stock i on day t, $r_{m,t}$ is the value- weighted excess market index return on day t, σ_i^2 is the variance of stock i, $r_{m,t}$is the covariance between$r_{i,t}$ and $r_{m,t}$, and σ_m^2 m is the variance of $r_{m,t}$. $R_{i,d}$is the return of stock$i$ on day t, $Volume_{i,t}$ is the trading volume of stock i on day t, and $D_{i[t_1,t_2]}$ is the number of days over the event period from t_1 to t_2 .

In Table 2, we find that firms with smaller sizes have higher estimated values of both idiosyncratic risk and illiquidity ratio compared to firms with larger sizes before both earnings announcements and M&A announcements. The higher idiosyncratic risk implies that small firms may induce more informed trading based on private information than large firms. And firms with higher illiquidity ratio implies that the price impact of informed trading is higher for small firms than large ones. In general, the result on firm size suggests that small firms may have higher level of information asymmetry. Since higher level of information asymmetry may lead to higher level of informed trading, we believe the result is supportive to our second hypothesis (*H2*: The levels of informed trading prior to corporate announcements are higher for small firms than for large firms). By further analyzing the results, we find the difference of the estimates across size is generally greater before M&A announcements than earnings announcements (e.g., the results of idiosyncratic risk in the period of [-25,-1]: the difference between large and small size firm is 0.0109 for earnings announcements and 0.0308 for M&A announcements). This suggests that he influence of firm size on the level of informed trading is more obvious for M&A announcements than earnings announcements. The second finding of the information asymmetry across companies with different profitability is still consistent with our third hypothesis (*H3*: The levels of informed trading prior to acquisition announcements are higher for poor financial performance acquiring firms than for good financial performance acquiring firms.).

Table 2: **Information Asymmetry around Announcement Events**

Panel A : Information Asymmetry around Earnings Announcements

Groups/Period	Size: Large	Size: Medium	Size: Small	Profitability: High	Profitability: Medium	Profitability: Low
	Idiosyncratic risk					
[-50,-26]	0.0635	0.0712	0.0744	0.0584	0.0703	0.0782
	(1.80*)	(2.31**)	(2.40**)	(1.92**)	(2.77***)	(2.93***)
[-25,-1]	0.0647	0.0709	0.0756	0.0589	0.0684	0.0820
	(2.28**)	(2.59***)	(2.94***)	(2.89***)	(2.76***)	(4.14***)
[1,25]	0.0637	0.0674	0.0745	0.0618	0.0677	0.0754
	(2.64***)	(2.88***)	(3.01***)	(2.63***)	(2.90***)	(3.42***)
[26,50]	0.0612	0.0669	0.0725	0.0607	0.0650	0.0719
	(1.72*)	(2.25**)	(2.33**)	(2.17**)	(2.52**)	(3.91***)
	Amihud's illiquidity ratio					
[-50,-26]	0.0237	0.0428	0.0567	0.0682	0.0332	0.0833
	(2.24**)	(2.38**)	(3.30***)	(2.10**)	(2.74***)	(2.98***)
[-25,-1]	0.0402	0.0508	0.0710	0.0603	0.0776	0.1280
	(2.25**)	(2.67***)	(3.00***)	(2.79***)	(2.81***)	(3.57***)
[1,25]	0.0518	0.0687	0.0843	0.0690	0.0877	0.1238
	(2.69***)	(2.81***)	(2.87***)	(2.78***)	(2.82***)	(3.15***)
[26,50]	0.0682	0.0793	0.0892	0.0712	0.0740	0.1036
	(2.05**)	(2.29**)	(3.56***)	(2.03**)	(2.35**)	(2.89***)

Panel B: Information Asymmetry around M&A Announcements

Groups/Period	Size: Large	Size: Medium	Size: Small	Profitability: High	Profitability: Medium	Profitability: Low
	Idiosyncratic risk					
[-50-,26]	0.0658	0.0757	0.0764	0.0661	0.0725	0.0813
	(1.69*)	(2.43**)	(2.69***)	(2.38**)	(3.17***)	(4.05***)
[-25,-1]	0.0472	0.0528	0.0780	0.0683	0.0734	0.0855
	(2.33**)	(2.67***)	(3.18***)	(3.29***)	(3.36***)	(4.67***)
[1,25]	0.0621	0.0664	0.0776	0.0637	0.0710	0.0813
	(2.90***)	(3.12***)	(3.54***)	(2.80***)	(3.23***)	(4.03***)
[26,50]	0.0632	0.0692	0.0749	0.0655	0.0712	0.0773
	(1.84**)	(2.21**)	(3.53***)	(2.30**)	(2.68***)	(3.71***)
	Amihud's illiquidity ratio					
[-50,26]	0.0458	0.0670	0.0936	0.0920	0.1023	0.1984
	(2.25**)	(2.40**)	(2.97***)	(2.05**)	(2.68***)	(3.17***)
[-25,-1]	0.0681	0.0920	0.1143	0.0948	0.1612	0.3280
	(2.31**)	(2.74***)	(3.16***)	(2.68***)	(2.73***)	(3.60***)
[1,25]	0.0731	0.1082	0.1395	0.0818	0.1574	0.2841
	(2.71***)	(2.72***)	(2.80***)	(2.73***)	(2.66***)	(3.97***)
[26,50]	0.0908	0.1220	0.1199	0.0934	0.1458	0.2015
	(1.99**)	(2.35**)	(3.02***)	(1.95**)	(2.01**)	(3.26***)

This table reports the level of information asymmetry before earnings announcements and M&A announcements. Panel A shows the information asymmetry before earnings accouterments and Panel B shows the information asymmetry before M&A accouterments. Each panel reports the results in 6 groups divided by firm size and profitability. We use idiosyncratic risk and Amihud's (2002) illiquidity ratio as the proxy for information asymmetry. Idiosyncratic risk is the standard deviation of the residuals of the market model. We estimate the idiosyncratic risk over the event period from -50 to -26 and from -25 to -1, respectively. Amihud's (2002) illiquidity ratio is measured as the ratio of absolute stock returns to trading volume. Using daily stock returns and trading volumes, we measure Amihud's illiquidity ratio over the event period from -50 to -26 and from -25 to -1, respectively. The results of each sized group are first calculated from every individual company and than averaged simply by numbers of companies in each group. T-statistics for the information asymmetry measures are also shown in this table. *, ** and *** indicate statistical significance at the 10%,5% and 1% level, respectively.

4.1.2 Cumulative Abnormal Returns around Announcements

Following Park et al. (2014) and Le et al. (2019), we use abnormal return (AR) and the cumulative abnormal return (CAR) as proxies to examine stock prices movements prior to earnings announcements and M&A announcements as follow:

$$CAR_{i,(t_1-t_2)} = \sum_{t=t_1}^{t_2} AR_{i,t} * 100 \tag{4}$$

where $AR_{i,t}$ is difference between logarithmic return for stock i and the market return on day t. Based on the market model, we use the logarithmic return of CSI300 Index (the value-weighted index of 300 largest listed companies in China) as a proxy for the market portfolio. $CAR_{i,(t_1-t_2)}$ is the cumulative abnormal return for stock i in the period from $t_1$to t_2.

Table 3 reports the mean CARs around the earnings and M&A announcements in the period of [-25,10]. Three findings can be observed from the results. First, cumulative abnormal return around M&A announcements are significantly positive while cumulative abnormal return around earnings announcements are close to zero. This is because the irrational beliefs about M&A transactions in China stock market lead to unreasonable postie return in stock prices. Second, we find the cumulative abnormal returns for small firms are greater than ones with larger sizes around M&A announcements. This is supportive to the second hypothesis (H2). Thirdly, some conclusions can be drawn that the profitability is another depending firm characteristic to identify informed trading (H3).

Table 3: Cumulative Abnormal Returns around Announcement Events

Panel A :Cumulative Abnormal Returns around Earnings Announcements

Group/Period	Size			Profitability		
	Large	Medium	Small	High	Medium	Low
[-25,-11]	0.087	0.031	0.087	0.774	0.0119	0.013
	(2.14**)	(1.99**)	(3.44***)	(2.10**)	(2.38**)	(3.37***)
[-10,-6]	0.028	0.028	0.056	1.093	0.0119	-0.035
	(3.05***)	(3.12***)	(3.92***)	(3.78***)	(3.46***)	(4.04***)
[-5,-1]	0.054	0.031	-0.016	2.314	0.0119	-0.896
	(2.96***)	(3.22***)	(-3.13***)	(2.78***)	(3.57***)	(4.38***)
[0,1]	0.088	0.031	-0.045	1.977	0.0119	-1.389
	(3.13***)	(3.20***)	(-4.54***)	(4.97***)	(5.51***)	(-8.85***)
[0,5]	0.031	0.004	0.032	2.300	0.0119	-1.904
	(3.14***)	(3.94***)	(5.16***)	(4.20***)	(3.99***)	(-6.31***)
[0,10]	0.007	0.066	0.027	2.854	0.0119	-2.512
	(4.75***)	(4.90***)	(5.08***)	(4.48***)	(3.97***)	(-4.36***)

Panel B: Cumulative Abnormal Returns around M&A Announcements

Groups/Period	Size			Profitability		
	Large	Medium	Small	High	Medium	Low
[-25,-11]	0.133	0.348	0.560	0.363	0.760	0.933
	(1.82*)	(2.05**)	(3.27***)	(2.11**)	(2.50**)	(2.68***)
[-10,-6]	0.225	0.703	0.981	0.398	0.997	1.165
	(3.23***)	(3.23***)	(3.17***)	(3.59***)	(3.46***)	(3.37***)
[-5,-1]	0.058	0.913	2.315	1.877	2.18	3.965
	(2.87***)	(3.28***)	(3.08***)	(2.60***)	(3.57***)	(3.15***)
[0,1]	2.174	2.651	4.394	2.540	3.24	6.213
	(2.79***)	(2.95***)	(4.03***)	(3.58***)	(2.43**)	(2.61**)
[0,5]	2.890	3.365	5.187	3.739	4.01	6.334
	(3.24***)	(3.31***)	(5.16***)	(3.73***)	(3.16***)	(2.87***)
[0,10]	3.453	3.367	4.560	5.092	4.41	5.890
	(3.77***)	(4.28***)	(5.08***)	(4.15***)	(3.30***)	(4.28***)

This table reports the mean cumulative abnormal returns (CARs) over six different event periods from day -25 to day 10,respectively. day 0 is the announcement date.Based on the market model, the logarithmic return of CSI300 Index (the value-weighted index of 300 largest listed companies in China) as a proxy for the market portfolio. Panel A shows the cumulative abnormal returns around earnings accouterments and Panel B shows the cumulative abnormal returns around M&A accouterments. Each panel reports the results in 6 groups divided by firm size and profitability. The results of each sized group are first calculated from every individual company and than averaged simply by numbers of companies in each group. T-statistics for the mean of cumulative abnormal returns are also shown in this table. *, ** and *** indicate statistical significance at the 10%,5% and 1% level, respectively.

4.1.3 Abnormal Turnover around Announcements

Chae (2005) finds that the trading volume decreases before the scheduled announcements because uninformed investors try to avoid trades initiated by informed investors. Following his work, we further investigate the abnormal trading volume around earnings announcements and M&A announcement. We calculate turnover (TO) of firm i on day t as follow:

$$TO_{i,t} = log\left(\frac{Trading\ Volume_{i,t}}{outstanding\ shares_{i,t}}\right) \tag{5}$$

$$\overline{TO}_i = \frac{\sum_{t=-26}^{-55} TO_{i,t}}{30} \tag{6}$$

$$CATO_{i,[t_1,t_2]} = \sum_{t=t_1}^{t_2} (TO_{i,t} - \overline{TO}_i) \tag{7}$$

where $Trading\ Volume_{i,t}$ is trading volume of stock i on day t and $outstanding\ shares_{i,t}$ is the number of outstanding shares of stock i on day t. $\overline{TO}_i$ is the the average turnover in the pre-event period of days -55 to -26 for stock i. And $CATO_{i,[t_1,t_2]}$ is the cumulative abnormal turnover for stock i during the time period from $t_1$to t_2.

Table 4 shows the cumulative abnormal trading volume across firms with different size and profitability around earnings announcements and M&A announcements. The results generally indicate similar supportive evidences of H2 and H3, in which are smaller size and lower profitability should be related with higher cumulative abnormal trading volume and more informed trading. And this effect also holds after the announcements in the time period of [0,5].

Table 4: **Cumulative Abnormal Turnover around Announcement Events**

Panel A :Cumulative Abnormal Turnover around Earnings Announcements

Groups/Period	Size			Profitability		
	Large	Medium	Small	High	Medium	Low
[-25,-11]	0.147	0.156	0.198	0.107	0.085	-0.073
	(1.48)	(1.77*)	(170*)	(2.33**)	(1.69*)	(2.53**)
[-10,-6]	0.113	0.178	0.240	0.108	0.127	-0.092
	(1.72*)	(2.36**)	(1.83*)	(2.84***)	(1.94**)	(2.00**)
[-5,-1]	0.153	0.190	0.310	0.124	0.117	-0.125
	(1.71*)	(1.98**)	(1.82*)	(2.79***)	(2.42**)	(2.90**)
[0,1]	0.1956	0.212	0.276	0.332	0.112	-0.206
	(3.12***)	(3.38***)	(3.25***)	(3.20***)	(2.68***)	(4.40***)
[1,5]	0.384	0.343	0.402	0.4185	0.200	-0.318
	(2.47**)	(2.31**)	(1.90**)	(2.03**)	(2.19**)	(3.90***)

Panel B: Cumulative Abnormal Turnover around M&A Announcements

Groups/Period	Size			Profitability		
	Large	Medium	Small	High	Medium	Low
[-25,-11]	0.085	0.1345	-0.105	0.157	0.011	-0.208
	(1.81*)	(2.16**)	(2.14**)	(2.03**)	(2.18**)	(2.69**)
[-10,-6]	0.071	-0.1467	-0.094	-0.032	-0.011	-0.135
	(2.07**)	(2.30**)	(2.38**)	(1.96**)	(2.54**)	(3.40***)
[-5,-1]	-0.063	-0.087	0.125	-0.085	-0.0113	0.306
	(2.14**)	(2.49**)	(2.12***)	(2.13**)	(2.49**)	(3.22***)
[0,1]	0.133	0.011	0.315	0.183	0.229	0.292
	(3.77***)	(3.51***)	(4.02***)	(4.44***)	(3.13***)	(5.81***)
[1,5]	0.322	0.013	1.107	0.490	0.645	0.843
	(3.07***)	(3.90***)	(3.41***)	(2.27**)	(3.68***)	(3.92***)

Panels A, B report the cumulative abnormal turnover around earnings accouterments and M&A accouterments,respectively. Each panel reports the results in 6 groups divided by firm size and profitability. Abnormal turnover (ATO) on day t is measured as the difference between the actual turnover on day t and the average turnover in the pre-event period (days from -55 to -26). Cumulative abnormal turnover (CATO) is the sum of ATO over the event period from t_1 to t_2 . Day 0 is the earnings announcement date. The results of each sized group are first calculated from every individual company, and then averaged simply by numbers of companies in each group. T-statistics for the mean of cumulative abnormal turnovers are also shown in this table. *, ** and *** indicate statistical significance at the 10%,5% and 1% level, respectively.

4.1.4 Trade Imbalance around Announcements

The trading volume does not show who buys (or sells) stocks with upcoming positive or negative earnings surprises. Following Malmendier and Shanthikumar (2007) and Lai and Teo (2008), we utilize a standardized trading imbalance in order to measure the direction of trading by each type of investor around earnings announcements. We first calculate the trade imbalance ($TI_{i,t}$) in Eq. (8), and then construct a standardized trade imbalance ($STI_{i,t}$) in Eq. (9). The cumulative standardized trade imbalance $\{CTI_{i[t_1,t_2]}\}$ in Eq. (10) as follow:

$$TI_{i,t} = \frac{Buy\ Volume_{i,t} - Sell\ Volume_{i,t}}{Buy\ Volume_{i,t} + Sell\ Volume_{i,t}} \tag{8}$$

$$STI_{i,t} = \frac{TI_{i,t} - TI_{i,year(t)}}{std(TI_{i,year(t)})} \tag{9}$$

$$CTI_{i[t_1,t_2]} = \sum_{t=t_1}^{t_2} STI_{i,t} \tag{10}$$

where $TI_{i,t}$ is trade imbalance of stock i on day t. $Buy\ Volume_{i,t}$ and $Sell\ Volume_{i,t} TI_{i,t}$ are the volume of stock i on day t from buyers initialed traders and sellers initialed traders, respectively. $STI_{i,t}$ is the standardized trade imbalance of stock i on day t; $TI_{i,year(t)}$ is the average trade imbalance of stock i over the one-year period prior to the event (trading days from -275 to -26), and $std(TI_{i,year(t)})$ is the standard deviation of trade imbalance over trading days -275 to -26. $CTI[t_1, t_2]_{i,t}$ is the cumulative trade imbalance for stock i in the period from $t_1$to day t_2.

The results of Table 5 are surprisingly different from the last three measures (Section 4.1.1, 4.1.2 and 4.1.3). We do not find obvious trade imbalances in most time periods for all groups before earnings and M&A announcements. Only in the period of [-5,-1], the results show the increase in trade imbalances. However, since the time period is right before announcements, it is dangerous to trade on private information for actual insiders. We believe that investors with insider information should prefer to trade in earlier period. And the investigation on simple trade imbalances could fail to capture investors choosing to camouflage (Barclay and Warner, 1993). Therefore, we suggest direct measures should be implemented in identifying the dynamic level of informed trading around announcements (Section 4.3).

Table 5: **Cumulative standardized trade imbalance (STI) around Announcement Events**

Panel A : Cumulative standardized trade imbalance Around Earnings Announcements

Groups/Period	Size			Profitability		
	Large	Medium	Small	High	Medium	Low
[-25,-11]	-0.013	-0.013	0.017	0.013	0.007	0.096
	(-0.35)	(-0.55)	(0.81)	(0.85)	(-0.72)	(1.68*)
[-10,-6]	-0.0123	-0.021	0.033	0.022	-0.013	0.014
	(-0.40)	(-0.49)	(1.23)	(1.90*)	(-0.89)	(1.72*)
[-5,-1]	0.047	0.087	0.016	0.058	0.021	0.041
	(0.77)	(0.96)	(2.40**)	(3.09***)	(1.94*)	(2.50**)
[0,1]	0.017	0.047	0.019	0.081	0.094	0.076
	(0.52)	(0.54)	(-1.55)	(4.86***)	(1.88*)	(1.98**)
[1,5]	0.036	0.024	0.048	0.056	0.066	0.112
	(0.36)	(0.49)	(-0.87)	(2.34**)	(1.38)	(2.01**)

Panel B: Cumulative standardized trade imbalance around M&A Announcements

Groups/Period	Size			Profitability		
	Large	Medium	Small	High	Medium	Low
[-25,-11]	-0.008	0.009	0.013	0.006	0.014	0.022
	(-0.56)	(0.65)	(0.59)	(0.77)	(1.24)	(1.69*)
[-10,-6]	-0.025	0.019	0.013	0.051	0.018	0.059
	(-0.68)	(0.92)	(1.32)	(1.74*)	(1.50)	(1.90*)
[-5,-1]	0.030	0.027	0.025	0.061	0.033	0.073
	(1.67*)	(1.80*)	(3.00***)	(2.70**)	(3.77***)	(6.48***)
[0,1]	0.038	0.032	0.050	0.126	0.025	0.17
	(2.88***)	(3.57***)	(6.57***)	(3.37***)	(4.26***)	(9.55***)
[1,5]	0.0134	0.029	0.044	0.078	0.054	0.0199
	(3.12***)	(6.18***)	(7.35***)	(1.90***)	(4.10***)	(6.21***)

Panels A, B report the cumulative standardized trade imbalances around earnings accouterments and M&A accouterments,respectively. Each panel reports the results in 6 groups divided by firm size and profitability. Day 0 is the earnings announcement date. The results of each sized group are first calculated from every individual company and than averaged simply by numbers of companies in each group. T-statistics for the mean of cumulative standardized trade imbalance are also shown in this table *, ** and *** indicate statistical significance at the 10%,5% and 1% level, respectively.

4.2 Predictability of Post-Announcement Abnormal return by Pre-Announcement Trading

To confirm our findings of the previous indirect evidences, we employ a regression approach to examine the relationship between pre-announcement trading and post-announcement abnormal return. We include cumulative abnormal return in the pre-announcement period to control for the reversal phenomenon that stock returns exhibit a predictable return-reversal behavior found by Jegadeesh (1990) and Lehmann (1990). Results are separately implemented by groups divided by firm size and profitability.

$$CAR[0,5]_{i,t} = \alpha_0 + \alpha_1 CTI[t_1, t_2]_{i,t} + \alpha_1 CAR[-t_1, t_2]_{i,t} + \varepsilon_{i,t} \tag{11}$$

where $CAR[0,5]_{i,t}$ is the cumulative abnormal return for stock i in the period from day -5 to day 0. $CTI[t_1,t_2]_{i,t}$ is the cumulative trade imbalance for stock i in the period from $t_1$to day t_2. $CAR[-t_1,t_2]_{i,t}$ is the cumulative abnormal return for stock i in the period from $t_1$to day t_2.

Table 6: **Predictability of Post-Announcement Abnormal return by Pre-Announcement Trading**

Panel A : Cumulative standardized trade imbalance Around Earnings Announcements						
Groups/Factors	Size			Profitability		
	Large	Medium	Small	High	Medium	Low
CAR[-25,-11]	0.000	-0.001	0.001	0.002	0.002	0.007
	(0.23)	(-0.21)	(1.86*)	(0.89)	(0.36)	(0.16)
CAR[-10,-6]	0.002	-0.001	0.002	0.013	0.005	0.008
	(0.33)	(-0.47)	(2.21**)	(1.96**)	(1.10)	(1.50*)
CAR[-5,-1]	0.009	0.004	0.016	0.003	0.007	0.026
	(1.71*)	(1.23)	(2.25**)	(2.56***)	(2.28**)	(4.46***)
CTI[-25,-11]	0.000	0.000	0.017	0.001	0.003	0.012
	(0.18)	(0.03)	(0.84)	(1.69*)	(0.74)	(1.79*)
CTI[-10,-6]	0.002	0.006	0.012	0.005	0.004	0.011
	(0.32)	(0.14)	(1.92**)	(2.01**)	(0.33)	(1.66*)
CTI[-5,-1]	0.003	0.002	0.005	0.005	0.010	0.022
	(0.29)	(2.15**)	(2.00**)	(2.75***)	(2.40*)	(3.88***)
Adjusted R^2(%)	1.47	1.32	1.29	1.51	1.30	1.69
N	1000	1000	1000	1000	1000	1000
Panel B: Cumulative standardized trade imbalance around M&A Announcements						
Groups/ Factors	Size			Profitability		
	Large	Medium	Small	High	Medium	Low
CAR[-25,-11]	0.008	0.002	0.002	-0.029	0.002	0.001
	(0.33)	(1.74*)	(1.72*)	(-1.70*)	(2.53**)	(2.01**)
CAR[-10,-6]	-0.008	0.006	0.002	0.003	0.008	0.008
	(-1.90*)	(1.90*)	(3.16***)	(1.83*)	(1.77**)	(2.30**)
CAR[-5,-1]	0.066	0.017	0.026	0.018	0.040	0.35
	(3.10***)	(2.97***)	(6.67***)	(7.25***)	(3.64***)	(8.07***)
CTI[-25,-11]	0.004	-0.004	0.000	0.019	0.018	0.005
	(1.68*)	(-1.69*)	(0.32)	(1.99**)	(2.32**)	(1.87*)
CTI[-10,-6]	0.007	0.011	0.006	0.006	0.004	0.001
	(1.69*)	(1.75*)	(0.45)	(1.84**)	(1.68**)	(1.79*)
CTI[-5,-1]	0.012	0.007	0.019	0.028	0.035	0.072
	(2.33**)	(2.18**)	(4.16***)	(6.20***)	(3.41***)	(7.81***)
Adjusted R^2(%)	0.81	0.87	0.88	0.94	0.97	1.04
N	210	210	210	210	210	210

This table reports the predictability post-announcement abnormal return by pre-announcement trading. Panels A, B report the results for earnings announcement and M&A announcement,respectively. Each panel reports the results in 6 groups divided by firm size and profitability. Day 0 is the earnings announcement date. The results of each sized group are first calculated from every individual company and then averaged simply by numbers of companies in each group. T-statistics for the mean of cumulative abnormal returns are also shown in this table *, ** and *** indicate statistical significance at the 10%,5% and 1% level, respectively.

The regression results in Table 6 report the predictability post-announcement abnormal return by pre-announcement tradings. Firstly, the CARs and CTIs in the period of [-5,-1] have prediction ability of the post-announcement returns. This is consistent with the findings from Park et al. (2014) and Le et al. (2019). We could draw the conclusion that the tradings prior to both earnings announcements and M&A announcements are likely to be informed tradings. Furthermore, we observe that the prediction ability of CARs and CTIs is stronger for M&A announcements than earnings announcements. This is opposite to our hypothesis (H1) that informed tradings are more pronounced before earnings announcements than before M&A announcements. We claim that it is still because of the camouflage activities. M&A contain more private information Hence, we perform direct measures of PIN and VDPIN-PI to further test our first hypothesis.

4.3 Informed Trading Measured by PIN and VDPIN-PI around Announcements

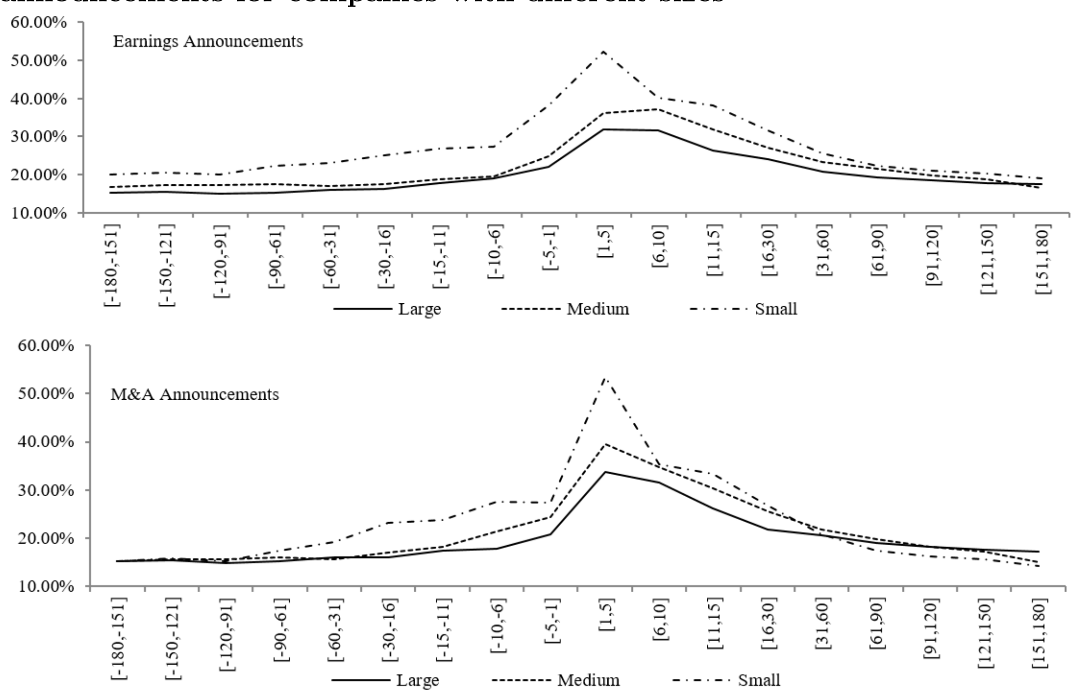
In this section, we aim to investigate the dynamic movements of level of informed trading around earnings and M&A announcements. As discussed in the previous chapter of the thesis, PIN measure introduced by Easley et al. (1996) is the most commonly applied measure in identifying informed trading. However, Duarte et al. (2020) argue the PIN do not match the variability of noise trade in the data and that this limitation has severe implications for how these models identify private information. Therefore, we believe that the Volume Weighted Dynamic Probability of Informed Trading of Price Impact (VDPIN-PI) developed in Chapter 2 could be a more efficient methodology when detecting informed trading, especially in exploring the dynamic changes around the announcements. Therefore, we apply both the PIN and VDPIN-PI as methodologies in verifying our hypotheses. Detailed explanation of our methodology can be found in Chapter 2, Section 5.2

4.3.1 Company Size and Informed Trading around Announcements

The levels of informed trading around earnings and M&A announcements across different sized companies by PIN and VDPIN-PI are shown in Figure 1 and Figure 2.

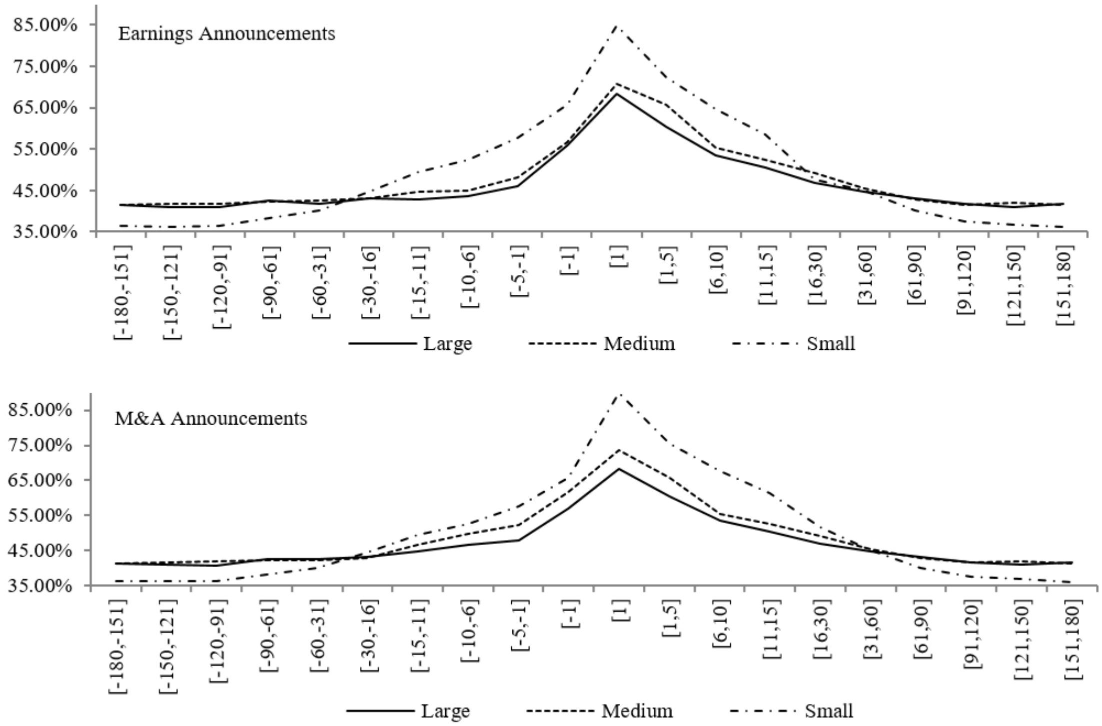
The results of PIN measure in Figure 1 show that firm size and level of informed trading are negatively related for both earnings and M&A announcements which consistent with the second hypothesis ($H2$). We also can observe the differences of informed trading level from small sized firms to other sized firms before earnings announcements are greater than ones before M&A announcements. Moreover, we suggest it is also importantly to observe the dynamic increase in the level of informed trading rather absolute proportions of each size group. To analyze the differences across different sized groups, we can observe that the increase of informed trading is much earlier and higher than the other twos. The level of informed trading increases since 90 days before the first announcements with the highest proportions over 55% for small companies. And the the level of informed trading increases since 60 days before the first announcements with the highest proportions lower than 40% for both large and medium companies. Additionally, there is a slight decreasing in the level of informed trading of small companies before M&A announcements in the period of [-10,-1]. Comparing to the results for the same group and period measured by VDPIN-PI in Figure 2, there is no decrease found.

Figure 1: Informed trading measured by PIN around Earnings and M&A announcements for companies with different sizes



This figure shows the level of informed trading measured by Easley PIN around announcements for companies with different sizes. The upper subfigure is the level of informed trading for large, medium and small companies for the 360-day event window which is consisted of both 180 days before and after the earnings accouterments. The lower figure is is the level of informed trading for large, medium and small companies before and after the M&A accouterments. The results of each sized group are first calculated from every individual company and than averaged simply by numbers of companies in each group.

Figure 2: Informed trading measured by VDPIN-PI around Earnings and M&A announcements for companies with different sizes



This figure shows the level of informed trading measured by VDPIN-PI around announcements for companies with different sizes. The upper subfigure is the level of informed trading for large, medium and small companies for the 360-day event window which is consisted of both 180 days before and after the earnings accouterments. The lower figure is is the level of informed trading for large, medium and small companies before and after the M&A accouterments. The results of each sized group are first calculated from every individual company and than averaged simply by numbers of companies in each group.

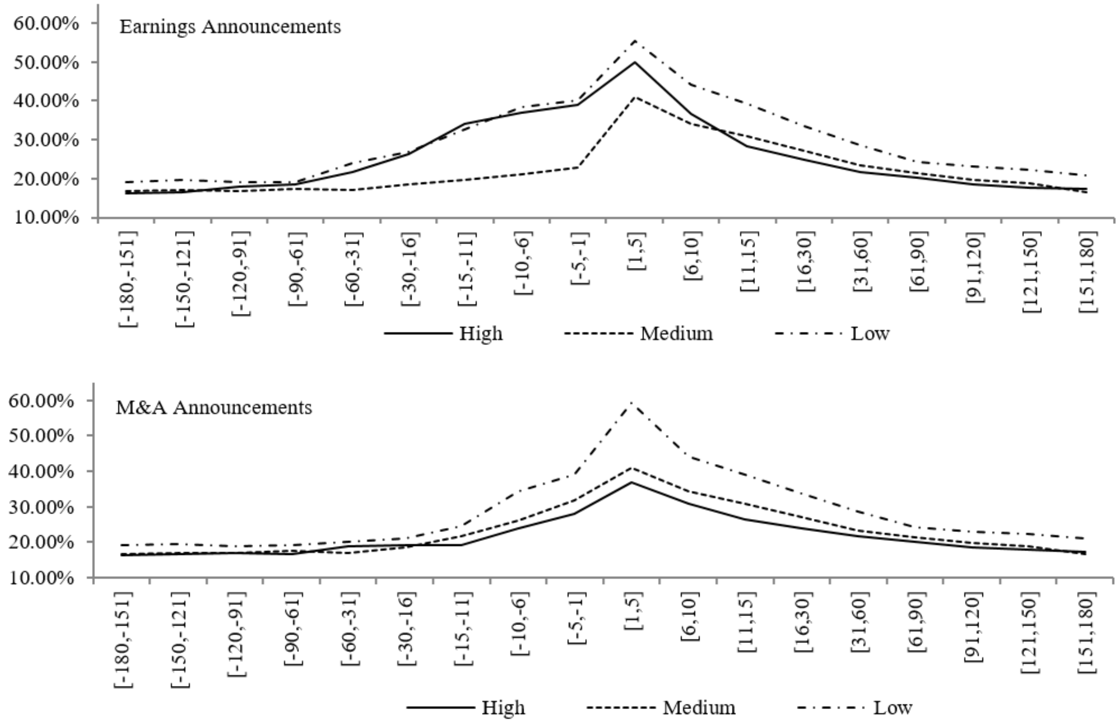
The informed trading captured by VDPIN-PI in the above figure basically shows similar results. Small companies have both highest absolute proportions and increase of informed tradings prior to the both earnings and M&A announcements. However, there are two main differences compared with the results from PIN. First, the level of informed trading of small companies in regular time (60days before and after announcements) is lower than large and medium companies. Second, we do not observe any decrease in the level of informed trading before the M&A announcements while there is a slight decrease in the window of [-10,-6] for small companies as discussed before. We believe that it is because of the different mechanism of these two methodologies. The key parameter of PIN measure is order imbalance which calculated as the difference in the numbers of buyer initialed trades and seller initialed trades. The VDPIN-PI considers not only the directions of trades but also the market trends. In the extremely sensitive time window which is within 10 days to the M&A announcements, insiders will not take great risk to cause significant price impact as it could be easily traced afterwards. It is more likely that insiders choose to camouflage by avoiding making obvious order imbalance or they have already finished most of their inventory building before this “dangerous” time window. Therefore, it is reasonable that the PIN (Easley et al., 1996) failed to catch any increase in the level of informed trading without an increase in the order imbalance. However, the VDPIN-PI should be able to detect a increase of informed trading if insiders still keep buying when the market is going down as discussed in Chapter 2. The results here are another proof of the advantage of the VDPIN-PI compared with the PIN (Easley et al., 1996). This somehow proves that information prior to M&A announcements is more private then earnings announcements.

4.3.2 Financial Performance and Informed Trading Around Announcements

In order to further test our third hypothesis ($H3$), we also employ PIN and VDPIN-PI to measure the level of informed trading around earnings and M&A announcements across companies with different profitability. Results are shown in Figure 3 and Figure 4.

From Figure 3, the results in the lower sub-figure, we can see that companies with both high and low profitability have higher level of informed trading than medium profitability companies measured by PIN. The level of informed trading measured by PIN before the earnings announcements is around 40% in the time window from [-10,-6] till [-5,-1] for both high and low profitability companies while the results of and medium profitability companies are lower than 25%. The difference among groups is more than 15%. Moreover, the groups of companies with both high and low profitability also show higher level of informed trading after the earnings announcement with the highest number over 50%. The results of medium groups are lower than 40%. This is clear evidence of the hypothesis *H3.* We argure that it could be because the fundamental information of earnings announcements is indeed the profitability of firms. Investors choose to trade on firms with either outstandingly good (gain profit) or bad (reduce losses) companies. Moreover, for the results before M&A announcements in the lower sub-figure, companies with high profitability show the lowest level of informed. A possible explanation is already discussed in previous section. As the irrational beliefs of retail investors about M&A transactions, managers would have strong intentions to launch a M&A in order to gain from insider tradings.

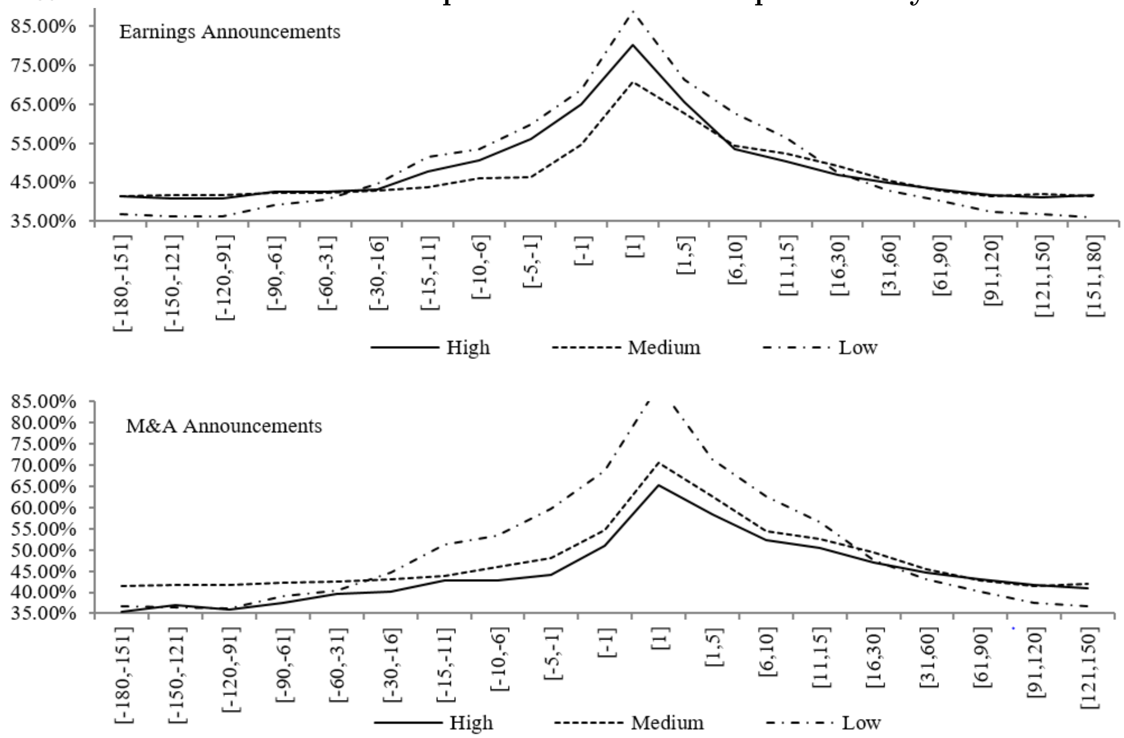
Figure 3: Informed trading measured by PIN around Earnings and M&A announcements for companies with different profitability



This figure shows the level of informed trading measured by PIN (Easley et al. 1996) around announcements for companies with profitability. The upper subfigure is the level of informed trading for high, medium and low profitability companies for the 360-day event window which is consisted of both 180 days before and after the earnings announcements.The lower figure is is the level of informed trading for high, medium and low profitability companies before and after the M&A accouterments. The results of each sized group are first calculated from every individual company and than averaged simply by numbers of companies in each group.

See from Figure 4, the methodologies of VDPIN-PI suggest almost similar results. Companies of both high and low profitability have more informed trading compared with companies of medium profitability ones before earnings announcements. And companies with lowest financial performance face more serious information leakage before M&A announcements than companies better financial performance. Additionally, we find all companies have information leakage problem before M&A announcements.

Figure 4: Informed trading measured by VDPIN-PI around Earnings and M&A announcements for companies with different profitability



This figure shows the level of informed trading measured by VDPIN-PI around announcements for companies with profitability. The upper subfigure is the level of informed trading for high, medium and low profitability companies for the 360-day event window which is consisted of both 180 days before and after the earnings announcements.The lower figure is is the level of informed trading for high, medium and low profitability companies before and after the M&A accouterments. The results of each sized group are first calculated from every individual company and than averaged simply by numbers of companies in each group.

Since hypothesis 2 and 3 has been fully verified based on current results. However, most methodologies give opposite results to hypothesis 1 showing that the levels of informed trading prior to scheduled earnings announcements are more pronounced than that prior to unscheduled M&A announcements. We consider this is because the information before M&A announcements than before earnings announcements. Since earnings announcements are scheduled, investor could make their own judgments based on macroeconomic indicates, industrial trend and past information of specific company. It is common that investors to trade by their judgments before the scheduled earnings announcements. A supportive evidence of this argument is that we find high level of informed trading in both good and bad companies, but low for medium companies. However, compared with earnings announcements, the M&A announcements are unscheduled and should remain private with prefect corporate governance about information leakage. Even there are always insiders who attempt to gain form insider information, they should try to camouflage as careful as they can. Essentially, the opposite results for hypothesis 1 is because our data and methodologies fail to distinguish between informed tradings and insider tradings. Nevertheless, it is reasonable to argue the increased level of informed tradings we captured are more likely to be insider tradings.

4.4 Relationship of Firm Characteristics and Informed Trading

Following the work of Aslan (2011), we implement the Fama–MacBeth (1973) regressions to test whether size and profitability are significant firm characteristics which may influence the level of informed trading. Different from the work of Aslan (2011), we aim to study informed trading around M&As rather than asset pricing. Results of the Unconditional probability of information-based trading (PIN) and the Volume Weighted Dynamic Probability of Informed Trading of Price Impact (VDPIN-PI) from the last Section 4.3 are used as the dependent variables and firm charismatics including size and profitability are independent variables in the following regression:

$$InT = \alpha_1 + \alpha_2 LogSize + \alpha_3 Roe + \alpha_4 Leverage + \alpha_5 RS + \alpha_6 CSI300 + \varepsilon$$

where InT is the level of informed trading measured by PIN and VDPIN-PI. $LogSize$ is the logarithm of the market value of equity for each firm in millions and Roe is the return on equity. $Leverage$ is debt/equity ratio and RS is the fraction of restricted shares should are not allowed to trade in the market. CSI300 is for membership in the CSI300 index for stock i for year t.

Table 7: **Test the Relationship of Firm Characteristics and the Level of Informed Trading**

		PIN		VDPIN-PI	
		Earnings Announcements	M&A Announcements	Earnings Announcements	M&A Announcements
1	LogSize	-1.542	-2.460	-1.677	-2.954
		(6.19***)	(8.56***)	(5.71***)	(6.02***)
2	Roe	-0.003	-0.118	-0.006	-0.062
		(0.12)	(3.51***)	(0.67)	(8.70***)
3	Leverage	0.033	0.076	0.017	0.052
		(1.71*)	(0.52)	(1.51)	(0.89)
4	RS	1.784	2.609	1.651	4.952
		(7.17***)	(6.54***)	(8.49***)	(4.80***)
5	CSI300	-5.01	-3.27	-4.55	-2.97
		(-3.55***)	(-3.08***)	(-3.26***)	(-3.20***)
	R^2	0.78	0.65	0.83	0.66

From Table 7, it can be seen that the key variables, $LogSize$ and Roe, are negatively correlated with InT at the significant level of 1%. These are strong supportive evidences of our hypothesis *2 and* 3. Moreover, we also find that fraction of restricted shares, and CSI300 dummy are also significantly related with the level of informed trading.

5 Robustness Tests

5.1 Actual Insider Trading Event Study

One of the most persuasive ways to test whether our methodology and results are dependable is to see whether same results can be achieved in insider trading events. Therefore, we pick three largest officially announced insider trading events during 2020 in this test as follow:

Table 8: **Informed trading of actual insider trading events around M&A announcements**

Stock Code	Name(short)	Announcement Date	Punishment Date	Forfeiture Amount	Penalty Amount
300248	XKP	01/07/2019	12/28/2020	21.15	42.31
600330	TTGF	05/24/2016	11/26/2020	5.24	15.71
300216	QSYJ	10/08/2018	12/24/2020	3.62	10.86

	XKP		TTGF		QSYJ	
Time Window	Easley PIN	VDPIN-PI	Easley PIN	VDPIN-PI	Easley PIN	VDPIN-PI
[-60,-31]	25.31%	37.12%	25.23%	39.40%	19.31%	34.05%
[-30,-15]	27.45%	38.70%	25.70%	41.35%	23.45%	35.99%
[-15,-6]	31.32%	41.18%	26.18%	42.59%	27.32%	38.72%
[-5,-1]	38.93%	47.65%	25.66%	45.65%	31.93%	44.25%
[-1]	46.67%	58.02%	31.53%	55.41%	37.67%	54.63%
[1]	58.29%	78.65%	48.29%	68.34%	48.29%	64.98%
[1,5]	47.30%	66.13%	40.67%	59.80%	40.30%	61.32%
[6,15]	43.77%	54.40%	33.42%	50.29%	33.77%	51.52%
[16,30]	33.21%	46.33%	30.03%	48.49%	30.21%	43.78%
[31,60]	29.60%	41.29%	25.82%	42.76%	25.60%	38.54%

As limited by fund budget, only the data of 120-day event window is available in this test.

As can be seen from Table 8, we can firstly observe significant information leakage before the first announcement day for all three events by PIN and VDPIN-PI. The increase in level of informed trading starts from the time window of [-30,-15] and becomes conspicuous in the time window of [-5,-1]. The company XKP shows not only the highest (21.36%, 21.25% and 8.54 for three methodologies while the other two events show much lower results) but also the earliest (obvious change in the time window of [-30,15] while the other two events show clear increase in the time window of [-15,-6]) increase in the level of informed trading compared with TTGF and QSYJ. We suggest this is because the event of XKP informed trading are the most serious one with highest forfeiture amount. Therefore, this test shows that our methodologies should be able to provide similar results of in actual insider trading events. Meanwhile, it could also be a supportive evidence that the informed tradings before M&As which are captured in our main research are indeed informed tradings or even insider tradings.

5.2 Long Term Influences of M&As for Companies with Different Size, Profitability and Levels of Informed Trading

The second robustness tests we design is to long term influences of M&As for companies with different size, profitability and levels of informed trading as follow:

The evidences we find in previous chapters all lead to an identical conclusion that companies with smaller size and poor financial performance are more likely to be engaged with informed trading as a result of agency problem. The importance of corporate governance in merger and acquisition strategy has not attracted such attention particularly in China.

As can be seen in the upper panel of the above Table 9, M&As have positive short term influences on stock price for almost all companies. The short term increase in stock price for small companies is much higher than large and medium companies. However, the performance of long term stock price for small companies is much poorer than large and medium companies. Similar situation is worse for companies with high, medium and low level of informed trading. Companies with high level of informed trading have average 24.86% price increase in 15 days but only 12.30% in three years. There is a negative long term stock return for companies with high level of informed trading. Nevertheless, companies with medium level of informed trading have a slight long term price increase. The companies with low level of informed trading have steady and remarkable long term price increases.

Therefore, we suggest companies with smaller size, poorer financial performance and higher level of informed trading level gain less or even negative long term influences (3 years). The results are consistent with Rani et al.(2016) that firms with better corporate governance enjoy higher valuation. We should not draw the conclusion that M&As for wound harm the companies under poor financial performance based on current results. It could also because companies under poor financial performance are simply more difficult benefits form M&As as a result of its original dilemma. However, we believe it is still meaningful to ask whether M&As can actually help companies with small size and poor financial performance.

Table 9: **Analysis of 3 years stock return and financial performance after M&As**

			5 Days	15 Days	30 Days	3 Months	6 Months	1 Year	2 Years	3 Years
Cumulated Abnormal Stock Return ($r_i - r_m$)	Size	Large	7.84%	8.30%	8.72%	10.65%	12.01%	13.66%	17.18%	18.40%
		Medium	9.98%	12.35%	13.62%	13.12%	13.69%	14.00%	15.23%	15.90%
		Small	15.20%	19.63%	16.39%	17.45%	17.27%	15.44%	15.84%	14.32%
	Profitability	High	9.18%	10.76%	10.89%	11.73%	13.05%	15.73%	16.84%	18.85%
		Medium	9.74%	10.92%	11.33%	12.84%	13.76%	15.11%	16.15%	18.03%
		Low	10.57%	11.54%	12.88%	12.82%	13.60%	15.42%	16.74%	16.32%
	Informed Trading Level	High	24.86%	23.17%	17.05%	15.00%	13.81%	13.08%	11.87%	12.30%
		Medium	14.11%	15.23%	14.39%	12.95%	13.66%	14.90%	15.24%	16.11%
		Low	7.05%	7.46%	8.10%	8.42%	11.76%	15.08%	16.99%	20.97%
			Year 0		Year 1		Year 2		Year 3	
			P/E	RoE	P/E	RoE	P/E	RoE	P/E	RoE
P/E Ratio/ RoE	Size	Large	11.23	12.12%	13.10	15.64%	14.18	15.79%	14.57	16.67%
		Medium	15.49	10.66%	18.42	13.12%	17.10	11.12%	18.01	10.06%
		Small	20.89	8.89%	26.84	13.39%	21.23	11.30%	18.34	8.78%
	Profitability	High	10.74	18.24%	11.33	25.80%	11.68	27.14%	12.25	29.31%
		Medium	13.20	13.17%	16.54	19.31%	15.32	15.43%	16.01	15.50%
		Low	25.12	7.30%	28.68	13.67%	22.33	10.05%	21.92	8.32%
	Informed Trading Level	High	26.56	5.34%	34.17	12.82%	20.12	6.92%	18.75	5.37%
		Medium	13.39	13.02%	18.31	20.91%	18.65	16.93%	20.00	16.89%
		Low	9.20	15.29%	12.40	19.22%	12.40	21.34%	13.20	21.98%

The accumulated abnormal stock price is calculated as follow: Firstly, calculate accumulated stock return by using the ending price of each period minus the 6 months average stock price before the first announcement day. Second, take out the market return of each period to have the accumulated abnormal return of each stock (Since there is a significant market crash in 2015, all stocks experienced huge decrease in the stock price. And stocks listed at different exchange market showed diversified price movements after the crash. Therefore, we take the different index return where the individual stock belongs to be the proxy of market return including the Shanghai Composite Index, Shenzhen Composite Index and the Growth Enterprise Index). Finally, calculate the return into percentage for the convenience of comparing.

6 Conclusion

This study attempts to identify informed trading around earnings and M&A announcements in China stock market. By employing both indirect and direct measures, we manage to verify our hypotheses: *1.* Informed tradings are more pronounced before earnings announcements than before M&A announcements. *2.* Informed tradings prior to earnings announcements tend to be non-insider tradings while informed tradings prior to M&A announcements tend to be actual insider tradings. *3.* Smaller companies have more informed trading before both earnings announcements and M&A announcements. *4.* Companies of both high and low profitability have more informed tradings compared with companies of medium profitability before earnings announcements. Nevertheless, only companies with poor financial performances have higher levels of informed tradings before M&A announcements.

As there seems to be an increase in the amount of insider trading cases like 'Ye Fei event'[4] in China stock market, we believe that it is meaningful and urgent to study on informed trading and insider trading in China. 'Ye Fei event' somehow provided an indirect support of our study as most of the insider trading activities that revealed are related with M&As or significant company announcements. Huge profits drive insiders to manipulate on stock price and even M&As themselves. This harms not only the interests of regular investors in the stock market but also the long term development of listed companies. Based on this, the first and most important contribution of our study is to provide a possible way for regulators in identifying informed or insider tradings during informational company events (especially the methodology of VDPIN-PI). Second, we bring the insight for the investor with sufficient and rational analysis could be adopted when investing in small and non-profitable companies. Instead of risky speculation based on fake or out-dated private information, the fundamentals of companies, foresight of industries and understanding of macroeconomic environment are more safe and reasonable. Finally, in the area of corporate governance, we stress that an unhealthy M&A which aiming at the insider trading gains is very likely to be harmful. Companies under poor-profitability situation should care more about the agency problem. Strict actions should be implemented ensuring that the managers always consider the long term interests of the companies as the first priority in making important decisions.

[4]The former Chinese huge fund manager, Ye Fei, unearthed 11 listed companies of insider trading and market manipulation on 13 May 2021. After investigation, the CSRC reported that listed company ZYJJ (603709) and LTDZ (603629) are committed guilty.

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Conclusion

The thesis starts from identifying similar U-shaped intraday patterns of trading volume, price discovery and levels of informed tradings in China's stock market using high-frequency data of the 300 component stocks of the CSI300 Index. We first attempt to seek explanations for these trading patterns, which have also been documented in other markets. Literature suggests that liquidity cost is one of the important factors explaining why investors prefer to concentrate their trades at the openning and ending periods of a day. We apply six liquidity measures including absolute spread, effective spread, relative spread, depth, Rupee depth and Amihud ratio to measure liquidity cost over a day. No evidence of lower liquidity cost in the first and last half hour of a trading day is documented. This is somehow expected, as a large number of retail investors in China generate extremely high trading volume and turnovers throughout the trading time. Therefore, liquidity is less likely a concern for traders in China. We turn to seek for alternative explanations. The combined results of intraday patterns of price discovery and levels of informed tradings as well as momentum effect of informed trading within a day shed lights on alternative reasons, i,e, the abnormal returns casued by unbalanced information flow throughout a day, that can better explain the intraday U-shaped trading patterns.

To gain more solid and multi-dimensional evidence that can support our hypothesis, we further study on intraday informed trading patterns in the second empirical chapter. Contrarian trades have been proposed and applied by many studies to represent informed trades. Drehmann et al. (2005) suggest that investors with private information frequently act as contrarians. We investigate informed trades on the CSI300 component stocks in China's market by first applying the baseline measure (VDPIN), which uses contrarian trades to proxy for informed trades. Next, we improve the modeling of informed trades by explicitly incorporating the price impact exerted by large-sized trades, which may affect the detection of informed trades by uniformly using contrarian trades for all trade sizes. The modified model, that is, VDPIN-PI that accommodates large trade price impact, is found to be able to capture informed tradings more effectively, as confirmed by the robustness tests. Our results based on the modified informed trading model are generally consistent with the predictions of Admati and Pfleiderer (1988) regarding intraday patterns of volume and price variability, that is, informed (and liquidity) trading should concentrate at the opening and closing time of a day.

Another strand of the informed trading literature argues that informed traders would try to camouflage, which means they may split large trades into medium-sized orders to mitigate the price impact cost. Then, the trade size strategy of informed traders become a trade-off between information delay and price impact cost. Hence, an examination of informed trades of different trade sizes is essential to facilitate better understanding of informed trading strategies. By examining different trade size categories, we find that informed trades of different trade sizes are heterogeneous within a day, with only informed trades of medium-sized orders showing the similar intraday pattern with that of the aggregate informed trading. This provides support to the widely-held belief that informed traders camouflage their information by spliting large trades into medium-sized orders.

In addition, we conduct a predictability test to seek other possible causes that explain the detected intraday pattern of informed trading. The results from the predictability analysis, especially of the intervals with large-sized trades, imply that the informed trading at market close is driven not only by information retained from early morning (late-informed trading) but also by private information supposed to arrive the next day. This finding provides new insights for the high informed trading found at market close. In this way, we include two new dimensions, that is, trade size compositions and informed trading predictability, in the empirical investigation and explanation of the intraday U-shape pattern of informed trading.

In addition to research on informed tradings at the aggregate market level, in the last empirical chapter we extend it to study informed tradings around firm level events such as earnings and M&A announcements. By employing both indirect and direct informed trading measures, we find a series of empirical evidence in support of our hypotheses: *1.* Informed tradings are more pronounced before earnings announcements than before M&A announcements. *2.* Informed tradings prior to earnings announcements tend to be non-insider tradings while informed tradings prior to M&A announcements tend to be actual insider tradings. *3.* Smaller companies have more informed trading before both earnings announcements and M&A announcements. *4.* Companies of both high and low profitability have more informed tradings than companies of medium profitability before earnings announcements. Nevertheless, only companies with poor financial performances have higher levels of informed tradings before M&A announcements.

These results have important implications. First, they provide a way for regulators to efficiently identify informed trades based on insider information during informational company events, such as earnings announcement and M&A announcements. Second, our research shed lights on a series of driving factors, such as insider information, weak external monitoring and regulation, agency problem, that can explain informed trades on small and non-profitable companies. Finally, in terms of corporate governance, our findings suggest that unhealthy M&A plans aiming at insider trading profits is harmful to shareholders and companies of poor-profitability is more likely to engage in such unhealthy M&As due to agency problems. Actions must be in place to prohibit managers from engaging in such M&As.

Future Works

As restricted by time, budget and technology, this research also faces several limitations which are difficult to be improved in a short future. Nevertheless, for further study and research, we would like to discuss about three problems which are worthy to be modified as follow:

Data Related Issues

Most of the data we implied in this research is high-frequency data. It is indeed interesting and meaningful to study on high-frequency data. However, processing high-frequency data is quite technology demanding and time consuming. Majority of our time and vitality was spent in running tests and simulations. Moreover, the computing capacity as well as the read-write speed of the research device are also important. With the development of cloud computing technology, the efficiency of research based on high-frequency data should be able enjoy a significant improvement. If the data storage and computing process can be uploaded onto the cloud servers, it should not only save half of our time and also create huge new possibilities of our research. Another important limitation of high-frequency data is the expensive price. The CSI 300 is not the most suitable data for study of informed trading. Limited by our budget, only 90 stocks with different sizes are achieved as our second set of data. We believe that a larger data set with more stock and longer period could broaden our research.

Lack of causality relationship research

This research mainly focuses on identifying phenomenons such as intraday patterns of informed trading or informed trading anomaly around M&A events as well finding reasonable explanations for them. However, we believe that this research could offer higher contribution if we can further seek the causality relationship between these phenomenons. For instance, an impulse-response function or vector auto-regression model could be implemented testing the causality relationship between company characteristics and informed trading activities.

Need for across-market comparison

This research fully focuses on China stock market only. As discussed before, China stock market is general to be a large but less developed and weak regulated emerging market. It is doubtful that the methodology we modified and results we achieved in China stock market can still hold when applying them to other developed markets.

We do hope that there is a chance for the limitations above as well as any undiscovered problems in this research can be improved or solved in the future.

Appendix

List of Figures

Chapter 1

Figure 1： Intraday Patterns of Volume and Trades.. 17
Figure 2： Intraday Patterns of Return and Volatility.. 18
Figure 3： Intraday Patterns of Spread and Depth..20
Figure 4： Intraday Patterns of Amihud illiquidity Ratio and Flow Ratio.................................... 22
Figure 5： Intraday Patterns of Informed Trading...25
Figure 6： Intraday patterns of Price Discovery.. 26
Figure 7： Intraday patterns of Price Discovery including aggregate auction period for large medium and small..27
Figure 8： The results of Profit Seeking Test.. 28

Chapter 2

Figure 1： Intraday Informed Trades Measured by Baseline VDPIN and VDPIN-PI.................. 43
Figure 2： Intraday Informed Trades Measured by Baseline VDPIN for Small, medium, and Large Trades... 44
Figure 3： Intraday Average Numbers Of Trades, Trade Sizes and Intraday Proportions for Small, Medium, and Large Trades...46
Figure 4： Tree Diagram of Impact and Non-Impact Intervals.. 50
Figure 5： Intraday Informed Trades Measured by VDPIN-PI for Small, Medium and Large Trades...51
Figure 6： Intraday Pattern Of Proportion Of Trades With Information Advantage..................... 59

Chapter 3

Figure 1： Informed trading measured by PIN around Earnings and M&A announcements for companies with different sizes 88
Figure 2： informed trading measured by VDPIN-PI around Earnings and M&A announcements for companies with different sizes.. 89

Figure 3: Informed trading measured by PIN around Earnings and M&A announcements for companies with different profitability.....91
Figure 4: Informed trading measured by VDPIN-PI around Earnings and M&A announcements for companies with different profitability.....92

List of Tables

Chapter 1

Table 1: Regression Results of Intraday Momentum Test.....25

Chapter 2

Table 1: Summary Statistics on Trades and Interval Returns.....40
Table 2: Percentage Price Impact, Unexpected Return, and Trade imbalance.....48
Table 3: Informed Trades of VDPIN and VDPIN-PI across Trade Sizes.....52
Table 4: Unexpected Return Predictability.....54
Table 5: Autocorrelation Test for Intervals with Large Trades.....57
Table 6: Accumulated Returns of Informed Tradings Measured By VDPIN and VDPIN-PI.... 59

Chapter 3

Table 1: Descriptive Statistics of Announcement Events 76
Table 2: Information Asymmetry around Announcement Events 79
Table 3: Cumulative Abnormal Returns around Announcement Events 81
Table 4: Cumulative Abnormal Turnover around Announcement Events.....83
Table 5: Cumulative Trade imbalance around Announcement Events 85
Table 6: Predictability of Post-Announcement Abnormal return by Pre-Announcement Trading 86
Table 7: Test the Relationship of Firm Characteristics and the Level of Informed Trading 93
Table 8: Informed trading of actual insider trading events around M&A announcements.....94
Table 9: Analysis of 3 Years Stock Return and Financial performance after M&As..... 96