The Impacts of Margin-trading and Short-selling on Liquidity: Evidence from the Chinese Stock Market

Thesis submitted in accordance with the requirements of the University of Liverpool for the degree of Doctor in Philosophy by

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Declaration

This thesis is my original work and has not been presented in any other university.

The material contained in the thesis has not been previously submitted.

Abstract

Margin-trading and short-selling activities in the Chinese stock market are unique in that only part of stocks are eligible for margin-trading and short-selling and the list of stocks that are eligible for margin-trading and short-selling changes over time. In addition, daily data on margin trading and short selling activities are available for each individual stock.

Taking advantage of this market design and using daily data from March 2010 to the end of 2016, I firstly show that stocks' eligibility on margin trading and short selling contributes to improvement in stock liquidity as measured by effective spread and Amihud's (2002) Illiquidity Ratio. Secondly, to differentiate the impacts of margin trading and short selling, I find that margin-trading enhances liquidity while short selling impairs liquidity. In addition, I prove that the detrimental effect of short-selling on liquidity is due to it increases the adverse selection risk of the relevant stocks. Results suggest that short-sellers are informed traders as short-selling have predictive power on returns. In addition, short-selling in stocks with highest information asymmetry level tend to have the strongest negative impact on stock liquidity. Thirdly, I also demonstrate the asymmetry impacts of margin-trading and short-selling in different market conditions. At poor market conditions, stocks eligible for margin-trading and short-selling tend to have lower liquidity rather than higher liquidity. Furthermore, margin-trading activity hinders liquidity but short-selling improves liquidity. Hence, the impacts of margin trading and short selling on liquidity reversed during the market downturns. My finding helps to reconcile the discrepancy between many literature findings and regulators' policy of short selling ban during market crisis period.

I also examine the impacts of margin trading and short selling on the lead-lag relations in liquidity and return between stocks eligible for margin-trading and short selling and other stocks. Firstly, applying the Vector Autoregression (VAR) models on minute data, I find a strong lead-lag relation in both liquidity and return between eligible stocks and ineligible stocks. That is, liquidity and returns for eligible stocks lead those of the ineligible stocks. This lead-lag effect persists under different market conditions. In addition, the lead-lag effect in liquidity is stronger when investors are facing constrained funding liquidity which supports the theoretical model of Brunnermeier and Pedersen (2009) which suggests the interaction between funding liquidity and stock liquidity. Secondly, only margin trading has significant impacts on the lead-lag relations. To explain why the margin trading would have impact on lead-lag effects, I proposed three possible mechanisms (i.e., deleverage channel, cross-asset learning channel, and information diffusion channel) and use mediation analysis to test the importance of each mechanism. I found that the deleverage channel accounts for 58.24% (70.73%) of the impacts from margin trading on lead-lag effect in liquidity (return). The information diffusion channel only explains 2.28% (0.86%) of total effect that margin trading has on lead-lag effect in liquidity (return). The cross asset learning channel can explain 39.58% (28.41%) of the impacts of margin trading on lead-lag in liquidity (return). Our study provides the first empirical evidence in literature on the lead-lag relation in liquidity. In addition, it is the first paper that demonstrates the existence of return lead-lag relation at intraday level. Finally, it highlights the role that margin trading played in forming such lead lag relations in both liquidity and return.

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List of Abbreviations

ADF	Augmented Dickey-Fuller Test
AIC	Akaike information Criterion
AR	Autoregression
BIC	Bayesian Information Criterion
CSDC	China Securities Depository and Clearing Corporation
CSMAR	China Stock Market& Accounting Research
CSRC	China Securities Regulatory Commission
HS300	HuShen 300 Index
PBoC	People's Bank of China
PSM	Propensity Score Matching
SAC	Security Association of China
SCI	Shanghai Composite Index
SZSE	ShenZhen Stock Exchange
SSE	Shanghai Stock Exchange
VAR	Vector Autoregression
ZZ500	ZhongZheng 500 Index

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CHAPTER 1: INTRODUCTION

1.1 Overview

"As a method to enhance the innovation of credit trading mechanism in the Chinese security market, margin trading and short selling could enhance the market trading and investing activities."[1] Fulin Shang, the chairman of the Chinese Securities Regulatory Commission (CSRC), believed that introducing leverage trading could contribute to the Chinese stock market. As two leverage trading activities, margin-trading and short-selling have usually played essential roles in stock markets; they affect stock's liquidity, price discovery, and market efficiency. Margin-trading is a financing service in which security companies lend funds for investors to buy stocks. When investors short-sell stocks, they just sell those that have been borrowed from security companies. Both leverage trading activities need to use stocks and capital as collaterals and pay back fund and stocks on time to security companies. Despite margin trading and short selling behaviours being relatively new to the Chinese market, they have been widely performed in most developed countries' stock markets for around a century already, and have served different market participants for specific aims. For investors, they use margin-trading for profit in upward market trends and short-selling for profit in declined ones. Market makers offer traders capital or stocks inventory to fulfil market-making functions. Portfolio managers also use short selling as part of hedging strategy to diversify potential risks. Amongst these purposes, the latter two do not anticipate

[1] Fulin Shang, the chairman of the Chinese Securities Regulatory Commission (CSRC), answered the questions from the journalist on October 16, 2006. Available at http://www.csrc.gov.cn/pub/newsite/hdjl/zxft/lsonlyft/200710/t20071021_95204.html

manipulating stock prices. However, the first purpose of short-sellers gaining profit from stock price decrease has drawn the most attention from media and the public. Some regulators and media have blamed short-sellers for causing market crash and exacerbating liquidity dry up during the financial crisis. During the 1930s, U.S. regulators had stated that short-selling leads to stock market crash, and had posed several bans and regulations on short-selling, with attempts to stabilise the market (Jones, 2012). More recently, regulators have ascribed price drops during the 2008 financial crisis to uncurbed short selling behaviour[2]. The United States and several European countries have imposed urgent bans on short-selling in order to stabilise the market.

On the contrary, theoretical models and empirical findings from various literature are inconsistent with regulators' standpoint. Most researchers have proposed that short-selling is not harmful to the stock market. Their attitudes toward it are positive; they believe that the trading mechanism can actually improve the completeness of the market. It has been predicted from theoretical models that bans on short-sale can inflate the price from its fundamental value, reduce price efficiency, and hamper stocks' liquidity (Miller, 1997; Jarrow, 1980; Diamond and Verrecchia, 1987). Researchers have also empirically proved that short-selling contributes to market stabilisation, correct stock overpricing, and market liquidity improvement (Akbas et al., 2008; Balasubramanian, 2008; Boehme et al., 2006; Boehmer et al., 2008; Beber and Pangano, 2013; Boehmer et al., 2013). They have argued that short-sale bans are either ineffective or even harmful to market quality, whilst impairing the price discovery process (Lioui, 2009; Saffi and Sigurdsson, 2011;

[2]SEC News Release 2008-211, 2008-235, 2008-238 (http://www.sec.gov/news/press/pressarchive/2008press.shtml)

Battalio and Schultz, 2011; Beber and Pagano, 2013; Boehmer et al., 2013; Alves et al., 2016; Helmes et al., 2017).

As for margin-trading's impact on the stock market, it has drawn less attention from various literature or regulators as compared to short-selling. Most research have focused only on the impact of changes in margin requirement, whilst only few have concentrated on margin-trading's direct impact on stock's liquidity. Seguin (1990) find that margin eligibility improves the market depth. Recently, Kahraman and Tookes (2017) investigate the India stock market and find that stocks eligible for margin-trading have higher liquidity.

Liquidity is a vital factor of the stock market. There are several liquidities: asset liquidity, market liquidity, financial market's liquidity, and financial institution's liquidity. An asset's liquidity can be regarded as the ease to convert the asset into legal tender like cash. Market liquidity, compared to asset liquidity, is a broader concept. It is the ease to trade an asset quickly at a reasonable price without any impact of new information on the asset's fundamental value. Financial market's liquidity is measured by the substitutability among different assets traded in the particular financial market, and how liquid each asset is. On the other hand, financial institution's liquidity depends on the ease of a financial institution that can cover mismatch between its assets and liabilities and to settle its obligations (Sarr and Lybek, 2002). Among these four types of liquidities, this thesis focuses on a stock's market liquidity, and it is also the main focus of many studies when referring to liquidity.

The liquidity can influence both firms and investors in several aspects. For firms, a stock's liquidity impacts their capital structure and dividend payout policies

(Frieder and Martell, 2006; Banerjee, Gatchev, and Spindt, 2007; Lipson and Mortal, 2009). It has been also argued that ownership structure and corporate governance are correlated to stock's liquidity (Heflin and Shaw, 2000; Lipson and Mortal, 2004; Lerner and Schoar, 2004; Brockman, Chung, and Yan, 2009; Cheung et al., 2015). More importantly, liquidity even affects investment opportunities through cost of capital (Butler, Grullon, and Weston, 2005; Becker-Blease and Paul, 2006). For investors, the importance of liquidity is evident as liquidity directly influences the profitability of investments or trading strategies. Liquidity is regarded as a source of investment risk for investors, which may affect stock returns (Amihud and Mendelson, 1986b; Pastor and Stambaugh, 2003; Liu, 2006; Bekaert, Harvey, and Lundblad, 2007; Baradarannia and Peat, 2013) and asset pricing (Amihud and Mendelson, 1986a). When institutional investors make stocks investment decisions, they also take a stock's liquidity into consideration (Chung and Zhang, 2011). Meanwhile, on an aggregate market level, market liquidity may determine the cost of raising external capital (Butler, Grullon and Weston, 2005) and affect investors' confidence in security markets (Chordia et al., 2001). It largely influences the stock market's efficiency in financial resources allocation.

Both margin-trading and short-selling could affect stock's liquidities. Theoretical models like Miller (1977) and Diamond and Verrecchia (1987) predict that imposing bans on short-selling could hinder the liquidity of stocks. Many empirical studies also support the prediction of these theoretical models and find that short-sale bans during the market crash period could actually decrease the liquidity (e.g. Beber and Pangano, 2013; Boehmer et al., 2013). Moreover, the work of Kahraman and Tookes (2017) suggests that margin-trading could improve stock's liquidity.

1.2 Research Questions

In China, margin-trading and short-selling are relatively new issues upon which few investigations have been conducted. Amongst these studies, most research have focused on the impact of such issues on returns and volatilities. For example, using two-year data of 285 stocks, Chang et al. (2014) find that price efficiency increases and volatility decreases when stocks are eligible for margin-trading and short-selling. In addition, short-selling activities are proved to be correlated with price efficiency enhancement and have the predictive power of future returns. However, they find no evidence to show that margin trading also has such predictive power. Findings from Chen et al. (2016) support margin-trading and short-selling's role to improve price efficiency. Similar results from Xiong et al. (2017) also suggest that price efficiency has been increased when stocks became eligible for short-selling. More recently, Li et al. (2018) utilise Propensity Score Matching (PSM) approach and monthly short-sale turnover, and find that short-selling improves both price efficiency and stock's liquidity.

This thesis will extend previous studies by including more stocks, expanding the sample period and utilising higher frequency data to further examine the impacts of margin-trading and short-selling on liquidities in China's stock market. This thesis is also different from previous literature like Sharif et al. (2014) and Li et al. (2018) which investigating the effect of margin-trading and short-selling on stock's liquidity in the ways of exploring the effect of margin-trading and short-selling. In their studies, they either only focus on the impact of lifting bans on margin-trading and short-selling, or just simply ascribe the liquidity improvement to short-selling while ignore the effect of margin-trading and reasons behind. Using a larger sample size consisting of daily high-frequency data for stocks listed in A-share markets from March 2010 to December 2016, this study can provide more accurate and comprehensive understanding of the impact of margin-trading and short-selling on market liquidity. Although margin-trading and short-selling had been initiated in China only from 2010 such that this study's time span may be shorter than comparative studies on the U.S. market, relevant data to be obtained are still believed to be sufficient to examine this question: to what extent does each activity (margin-trading and/or short-selling) influence stocks' liquidities in the Chinese market?

Moreover, the sample set already contains all eligible stocks for margin-trading and short-selling. Indeed, applying data from the Chinese market can help better understand the effect of margin-trading and short-selling than those using samples from the U.S. First, the Chinese stock market has very unique institutional settings and one of which is the gradual ban lifting process. Not all stocks in the Chinese stock market are eligible for margin-trading and short-selling; only those in a designated list can be sold short, with this list also changing over time. For example, in March 31st 2010, only 90 stocks were allowed for margin-trading and short-selling, while the remaining 2000 stocks were still ineligible stocks. After several years, in September 22nd 2014, 900 stocks were included in the list that allowed for margin-trading and short-selling. However, in most developed stock markets like U.S. and U.K. stock markets, there is no such designated list and almost all stocks can be margined or shorted freely. Take advantage of this unique market setting in China, this thesis can better examine the effect of lifting bans on margin-trading and short-selling. Another advantage of this thesis using the sample from the Chinese stock market is the timing. In the U.S., many studies utilise data after or around the financial crisis to test the impact of short-selling ban on liquidity. For example, Beber and Pagano (2013) cover 30 countries around the world, but focus only on the 2007–09 financial crisis period; they find that short-sale bans actually have a negative impact on liquidity and price efficiency. However, the financial crisis itself may influence liquidity either directly or indirectly. Liquidity changes may partly come from financial crisis incidences rather than constraints on short selling. In the bear market, short-selling trading tends to increase and liquidity typically declines, which enable people to be more prone to establish causal relationships between them. In contrast, there was no financial crisis or substantial market crash that had ever took place in China during the said period when margin-trading and short-selling were first allowed – although in 2015, a market crash happened that consisted a relatively small proportion of the sample period. Therefore, this study tends to suffer a less endogeneity problem. Owing to a longer sample period and a unique market structure, panel regressions have few confounding impacts from other events or factors. In addition, China has a more transparent data disclosure system – at least for margin-trading and short-selling – than the U.S., as all of its data on margin-trading and short-selling are required to be published on a daily basis. Consequently, my sample from the Chinese stock market contains more accurate information on margin-trading and short-selling; thus, the effects of these activities can be better investigated.

In addition, majority of previous studies from developed markets focus on the effect of short-selling bans on liquidity. However, in the Chinese stock market, margin trading dominates; hence, whether it contributes more to liquidity should also be investigated. Furthermore, the impact of margin-trading and short-selling on liquidity under the market crisis period will also be investigated.

In this thesis, in addition to the impacts on liquidity, I also examine the impacts of margin trading and short selling on the liquidity comovements between stocks with leveraged trading and other stocks. Recently, Hu, Liu, and Zhu (2019) utilise high-frequency data focusing on the market crash period in the Chinese stock market from June to September 2015 and find that under market crash period, a drop in prices of leverage-traded stocks, due to the increased the need of deleverage to meet margin requirements, lead to selling of other stocks in the intraday level. This study motivates me to investigate intra-day liquidities dynamics and lead-lag relations in liquidity between eligible and ineligible stocks. In this thesis, I examine lead-lag effect in intraday liquidities and returns between stocks that allowed for margin-trading and short-selling and stocks that are not allowed under extremely good and poor market conditions, using VAR estimation. Likewise, I investigate the reasons why the margin trading and short selling can contribute to lead-lag effects in liquidity and return. One reason that I propose could help explain the relation between leveraged trading and lead-lag effect is called “deleverage”. According to a theoretical model from Brunnermeier and Pedersen (2009), an investor’s funding liquidity and stock’s market liquidity relates and reinforces each other. When the price of a leverage-traded stock drops, an investor has to raise more capital in order to meet margin requirements. Under poor funding liquidity, he has to sell other unleveraged stocks in order to raise more capital. This may help explain the lead-lag effect in intraday liquidity and return between eligible and ineligible stocks. Apart from this reason, I also propose two more. One is “Information Diffusion Speed”, in which market- or industry-wide information are diffused at different speeds; some stocks like eligible ones have higher speeds, hence their prices react to new information faster than other stocks, which may cause lead-lag in liquidity and return (Hou and Moskowitz, 2005; Hou, 2007). The other reason is based on the "cross asset learning" theory from Cespa and Foucault (2014). Investors may use leverage-traded stocks as reference stocks whilst learning information about prices from leverage-traded stocks' liquidities and volatilities in order to make trading decisions on other stocks. In this thesis, I employ mediation analysis based on Preacher and Hayes (2004, 2008) to calculate how much each of the possible reasons mentioned above has contribute to the lead-lag effects in liquidity and return.

1.3 Main Findings and Contributions

My first empirical chapter of this thesis (i.e. Chapter 5) examines the determinants of liquidity in the Chinese stock market. I first test several determinants upon which impact on liquidity have been already proven in various literature (e.g. Stoll, 2000; Chordia, Roll, and Subrahmanyam, 2001; Chai, Faff, and Gharghori, 2010). The results from panel regression suggest that trading activities like price, volume, and volatility are still determinants of liquidity in the Chinese stock market. More importantly, I also consider some unique trading characteristics and regulations in my analysis. By including the status of option index listing, price limit hitting, and status of special treated in panel regressions, I confirm that these variables that represent the unique trading regulations in the Chinese stock market are likewise determinants of liquidity. The purpose of this chapter is two folds: firstly, I test the determinants of liquidity found in existing literature and to add in the unique determinants from the Chinese markets; secondly, to understand the determinants of liquidity in China in order to establish the basis regression specifications of liquidity for empirical analysis in future chapters.

My second empirical chapter (i.e. Chapter 6) investigates the impact of margin-trading and short-selling on stocks' liquidity. Taking advantage of unique market setting in the Chinese stock market that provides an ideal natural expriement for investigating the impact of leverage trading on stock's liquidity, I first show that stocks eligible for those activities tend to have lower effective spread and price impact, as measured by Amihud's Illiquid Ratio. The event study further establishes that after lifting bans on margin-trading and short-selling, liquidity of eligible stocks has improved. Results from both panel regression and event study are consistent with findings from previous studies in which lifting bans on margin-trading and short-selling can improve market quality (e.g. Beber and Pagano, 2013; Chang et al., 2014; Chen et al., 2016; Li et al., 2018). When focusing only on eligible stocks, I find that both position and turnover of margin-trading can improve stocks' liquidity. On the contrary, both position and turnover of short-selling can hamper liquidity. To explain the reason for short-selling's negative impact on liquidity, I assume the primary cause to be adverse selection. Therefore, I first prove that short-sellers are informed traders with short-sale position having a predictive power in return, whilst margin-trading has no such predictive power. Moreover, it is justified that for stocks with highest information asymmetry levels, their short-selling activities tend to have the strongest negative impact on liquidity. At last, I focus on the crisis period and find that stocks eligible for margin-trading and short-selling tend to have lower liquidity under a market crash period compared to a normal period. In addition, both activities' impact on liquidity also become very different during market crashes. Different from a normal period in which short-selling hinders liquidity, the said situation actually improves liquidity when market is under a poor condition whilst margin-trading decreases liquidity. This finding about the impact of short-selling is consistent with several theoretical and empirical findings from various literature, in which short-sale bans during a financial crisis impair market liquidity (e.g. Battalio and Schultz, 2011; Marsh and Payne, 2012; Beber and Pagano, 2013; Alves, Mendes, and da Silva, 2016).

Amongst all studies that investigate the impact of margin-trading and short-selling in the Chinese stock market, Chapter 6's analysis encompasses the largest sample size and the longest time span. This does not only focus on the impact of a stock's eligibility, but also on both the impact of margin-trading and short-selling. This also explains the reasons for the impact of short-selling on liquidity. Most importantly, this study reconciles discrepancies between literature findings and regulators' actions under a market crash period. According to literature, short-sale bans hamper information incorporation into prices, thus hindering price efficiency and liquidity. As for regulators, short-sale does have negative impact on liquidity. I prove both standpoints and find that the impacts of short-selling change with market conditions. For example, the results from panel regressions using a whole sample period suggest that short-selling has a detrimental impact on liquidity, which is consistent with regulators' viewpoints. Meanwhile, short-selling actually improves the liquidity of eligible stocks under a market crash period, which is consistent with literature findings. Therefore, I argue that imposing bans on short-sale during a market crisis cannot contribute to market liquidity improvement; rather, the impact of short-sale is not always positive. During a normal period, short-selling hampers stocks' liquidity.

My third empirical chapter (i.e. Chapter 7) focuses on the intra-day lead-lag relationship in liquidity and return between eligible and ineligible stocks. Using a VAR approach, I find a strong lead-lag in liquidities and in returns between eligible stocks and ineligible stocks. More specifically, stocks that are eligible for margin-trading and short-selling lead stocks that are ineligible for margin-trading or short-selling in both liquidity and return on an intraday level. These lead-lag relationships in liquidity and return also exist under different market conditions. To explain lead-lag effects in liquidity and return between eligible and ineligible stocks, I propose several channels and utilise mediation analysis to analyse said channels and study the mechanism behind the impacts of leveraged trading on lead-lag effect. Though I find that leverage trading can impact lead-lag effects directly and indirectly, only margin-trading contributes to the lead-lag effects in liquidity and return while short-selling has no significant explanation power. The first channel is a direct effect on leverage trading, so-called a "deleverage" effect, that accounts for 58.24% (70.73%) of the total impact of leverage trading on the lead-lag effect in liquidity (return). When investors are facing stricter funding liquidity (i.e. more difficult to raise capital), I find the lead-lag effect in liquidity becoming stronger. This result supports the theoretical model of Brunnermeier and Pedersen (2009) and is consistent with the findings of Hu, Liu, and Zhu (2019). The second is through "information diffusion speed" channel, only accounts for a small portion of the total impact (i.e. 2.28% (0.86%) of total impact of leverage trading on lead-lag in liquidity (return)), suggesting that lead-lag effect in liquidity and return is not mainly caused by speed of information diffusion. The third is through “cross asset learning” accounts for 39.58% (28.41%) of the total impact of leverage trading on lead-lag in liquidity (return).

Per my existing knowledge, this study is the first one that has used high-frequency data to investigate lead-lag effects in liquidity and return over a relatively long period. Moreover, it is the first to use mediation models to analyse how different channels helps explain the leverage trading’s impact on lead-lag effects. This study also shed light on the dynamics of liquidity comovement from an intraday aspect, thus complementing the existing literature by exploring the reasons behind lead-lag effects in liquidity and return.

1.4 Thesis Structure

This thesis is organised as follows:

In Chapter 2, literature related to liquidity measurements and determinants, and impact of margin-trading and short-selling are reviewed. Chapter 3 introduces the background information of margin-trading and short-selling activities in the Chinese stock market and their development processes. Chapter 4 describes data and variables employed in this thesis. Chapter 5 investigates the determinants of liquidity in the Chinese stock market, including those commonly used in various literature and those specific in the Chinese stock market. Chapter 6 empirically examines the impact of margin-trading and short-selling activities on stocks’ liquidity. Using high-frequency data, Chapter 7 focuses on the lead-lag relations in liquidity and in returns from an intraday aspect, as well as reasons leading to those lead-lag effects. Finally, Section 8 provides a summary of the main findings, including some limitations and proposed potential directions for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Measurements of Liquidity

There is no simple or unequivocal universal definition of liquidity, however, researchers agree that liquidity has different dimensions (Bernstein, 1987). For example, Garbade (1982), Kyle (1985), Holden (1990), and O'Hara (1997), propose that liquidity has three main dimensions: tightness, resiliency, and depth. Some other literature presents four di erent dimensions namely tightness, resilience, depth, and immediacy (Grossman and Miller, 1988; Harris, 1990). Later, Sarr and Lybek (2002) summarize that a liquid market has five dimensions: tightness, immediacy, depth, breadth, and resiliency. The tightness of the market is always measured by the cost that investors would accept for immediate trading. Resiliency measures the speed to correct any price stocks or order imbalance. Immediacy is highly related to resiliency while it is the speed of order execution and it measures the efficiency of transaction. Market depth is gauged by the volume being traded without a large deviation from bid price and ask price and is also related to demand pressure (Díaz and Escribano, 2020). Breadth refers to both the numbers of orders are numerous and trading volumes are large with minimal impact on trading prices. Among these dimensions, though each of them is different in nature, some of them are interrelated. For example, resiliency and immediacy are correlated in the way that a more resilient market can adjust the price to the normal level after a shock at a faster speed. Moreover, breadth and depth are interrelated as both dimensions depend on the number of orders traded at equilibrium prices. Therefore, researchers have to propose different liquidity measures to capture these different dimensions while some liquidity measures can be related to one another (e.g. Goyenko et al., 2009).

In most studies, the trading cost would be the most widely used measurement of liquidity which measures the tightness. The higher trading cost can reduce the return of investors. Trading cost can be split into two parts: the explicit and implicit. The former trading costs include broker commissions, transaction taxes, and settlement fees from the trading places and though these costs sometimes cannot be neglect, especially in the day-to-day trading, most researchers just focus on the implicit trading cost, which comes from the illiquidity of the market and measured using bid, ask and executive prices. In the early time research, spreads were proposed as the representative for the trading cost (Demsetz, 1968; Tinic, 1972; Benson and Hagerman, 1974; Stoll, 1978). Based on Demsetz's (1968) theory of transaction cost, the stock's liquidity is obtained from the liquidity demand's theory and it is the difference between the immediate bid and ask prices provided from the security dealer. Stoll (1978) proposed quoted spread and effective spread to measure the liquidity of a hypothetical transaction and the impact of a transaction on the price in the stock market. Spreads are one kind of transaction cost-based measurement for liquidity and have been used by various researchers in future studies. For example, in the studies of Christie and Schultz (1994), Huang and Stoll (1996), they both used several spreads calculated from the bid, ask, and trading prices as the liquidity measure. Among them, one of the most widely used spread measures is quoted spread.

Quoted Spread is defined as the difference between bid price b and ask price a.

$$\text{Quoted Spread} = a - b$$

In order to compare quoted spreads in a same basis, researchers calculate the relative quoted spread by normalized quoted spread with the mid-quote price m, the average of bid and ask price.

$$\text{Relative Quoted Spread (RQS)} = \frac{a-b}{m} = \frac{a-b}{(a+b)/2}$$

The quoted spread measurement is proved as a good measure of trading cost, especially for small orders. Fong, Holden, and Trzcinka (2017) proved that the relative quoted spread at closing is the best monthly and daily percent-cost proxy for liquidity if it is available. However, when the orders tend to be large orders, the weighted-average bid-ask spread is believed to be a better measurement by using the average bid and ask prices.

Another widely used transaction cost that measures the tightness is the effective spread. It has very similar definition as quoted spread. In a simple way, it is twice the difference between trading price and mid-quote price. However, the trading direction also matter when calculating the effective spread as the effective spread for k^{th} trade is defined mathematically as

$$\text{Effective Spread}_k = \begin{cases} 2(P_k - M_k), & \text{if } k^{\text{th}}\text{trade is a buy} \\ 2(M_k - P_k), & \text{if } k^{\text{th}}\text{trade is a sell} \end{cases}$$

where P_k is the trading price for k^{th} trade and M_k is the midpoint price at the time of the k^{th} trade. Then to make the effective spreads comparable, researchers sometimes calculate the relative effective spread by taking the logarithm of the prices (e.g. Chai, Faff and Gharghori, 2010). Researchers also simplify the definition as

$$\text{Relative Effective Spread}_k = 2 \cdot |\ln{(P_k)} - \ln{(M_k)}|$$

The effective spread is always used as the benchmark of liquidities, especially in the high-frequency data scenario. In the study of Fong, Holden and Trzcinka (2017), they use both relative quoted spread and relative effective spread as the liquidity benchmark. The volume-weighted average of effect spread is a good way to capture market liquidity. However, the calculation process would be very complicated and cost large amount of time.

Another measurement of spread is realized spread and it is calculated from liquidity supplier's side. The realized half-spread is defined as the difference between the transaction price and the mid-price at some time after the transaction. The time interval should be long enough to ensure that the market price can be adjusted to reflect the price impact (Huang and Stoll, 1996; Goyenko et al., 2009).

$$\text{Realized Spread}_k = \begin{cases} 2(P_k - M_{k+n}), & \text{if k}^{\text{th}}\text{trade is a buy} \\ 2(M_k - P_{k+n}), & \text{if k}^{\text{th}}\text{trade is a sell} \end{cases}$$

The spreads measures mentioned above can be calculated at both intraday level and daily or monthly, even annually level. Early literatures tend to use daily or monthly quoted spread based on end-of-day or end-of-month bid and ask prices. Recently, more researchers prefer using high-frequency data and obtain the spreads at intraday level. Goyenko et al., (2009) compared the monthly and annually spreads with the intraday high frequency spreads and suggested low frequency liquidity measures and high frequency measures are correlated. However, regardless the high-frequency or low-frequency data a researcher is used, the calculation of spreads requires both bid and ask prices. Sometimes, they are difficult to obtain, especially the bid and ask price at close are easy to be absent. To address this problem, Roll (1984) first propose an estimation for transaction cost that based on daily price changes instead of bid or ask prices. The estimation equals to twice the square root of covariance between price changes in day t and t-1, which has following specification:

$$\text{Roll}_i = 2\sqrt{-\,cov(\Delta p_t, \Delta p_{t-1})}$$

Roll (1984) argues that this measure could be a good estimation of effective spread.

Based on Roll's (1984) measure, Lesmond, Ogden and Trzcinka (1999) proposed a measurement using the maximum likelihood estimator for transaction cost for no trading price interval and they argue that this new measurement would perform as good as, or even better than the average effective spread. In their model, Lesmond, Ogden and Trzcinka (1999) estimate the "true return" R^*_{jt} based on measured returns R_{jt} using the following equation:

$$R^*_{jt} = \beta_j R_{mt} + \epsilon_{jt}$$

where

$R_{jt} = R^*_{jt} - \alpha_{1j}$ if $R^*_{jt} < \alpha_{1j}$

$R_{jt} = 0$ if $\alpha_{1j} < R^*_{jt} < \alpha_{2j}$

$R_{jt} = R^*_{jt} - \alpha_{2j}$ if $R^*_{jt} > \alpha_{2j}$

and R_{mt} is the market return while α_{1j} and α_{2j} are thresholds for trades on negative and positive information. The difference between the true return and measured return is the proportional transaction cost.

For larger orders, traders can move up or mover down the price and the price changes are related to the order sizes and the changes in the price are correlated to the average execution price, i.e. the weighted average bid-ask spread. A market in which investors can trade large size of orders without significantly moving the price is said to be "deep." Therefore, market depth is inversely related to the weighted average spread for large trade size.

Apart from the tightness, some researchers focused on the resiliency of liquidity, or price impact, which measures to what extent the price will change after a certain transaction. Amihud's (2002) Illiquidity ratio is a popular measurement of price impact, which followed the concept of liquidity by Kyle (1985). So for any stock on day t, its illiquidity ratio was defined as

$$\mathrm{ILLQI}_t = \frac{|R_t|}{Vol_t}$$

where R_t is the return for the stock on day t and Vol_t is the volume (in value) on that day. It was proved to be a good measurement of liquidity by several researchers. For example, Goyenko et al. (2009) and Hasbrouck (2009) found this illiquidity ratio perform well in measuring price impact. Marshall et al. (2011) also found it was highly related to liquidity benchmark. Moreover, in the emerging markets, it was one proxy that measures liquidity within individual country (Lesmond, 2005). Fong et. Al (2017) also argue that this is the best daily proxy for liquidity.

However, it is argued that the Illiquidity Ratio may have bias when dealing with cross-sectional data and be affected by the size of firms. It is natural that the trading volume tends to increase with the firm size so the Illiquidity Ratio would be affected if the sample contains firms with different sizes. Moreover, it fails to capture the trading frequency, which is an important aspect of liquidity. To address these problems, we use another measure for price impact, referred to price impact ratio, which is proposed by Florackis, Gregoriou, and Kostakis (2011). It is defined as the absolute average daily return to the turnover ratio.

$$\mathrm{PriceImpact}_t = \frac{|R_t|}{Turnover_t}$$

Sometimes, when the quote data are not available, researchers would use trading activity related data to measure the liquidity. For example, turnover is often used to measure the average holding period of stocks (Atkins and Dyl, 1997). Amihud and Mendelson (1986) also suggested that turnover is negatively related to spreads and positively related to liquidity, implying turnover could be used as measurement of liquidity. Another widely used measurement is trading volume; follow the intuition, the higher the trading volume, the more liquid the stock would be. However, both turnover and trading volume would be influenced by outside shocks like new information. Lesmond et, al. (1999) and Bekaert et, al. (2007) suggested that the frequency with no trading can be a proxy for illiquidity. For example, Lesmond, Ogden and Trzcinka (1999) propose two zero return measures, which captures both the tightness and depth of the liquidity. One measure uses the number of days with zero return over the total observations and the other is the ratio of the number of days with positive trading volume and zero return to the total observations. Similarly, Liu (2006) used turnover-adjusted number of zero daily trading volumes as a measure of illiquidity and focused on the trading speed. However, these zero-trading proxies are not good measurement of illiquidity in the Chinese stock market as daily trading volumes of every stock can never be zero[3].

2.2 Determinants of Liquidity

Many researchers using empirical evidences to propose that firm's trading characteristics can affect a stocks' liquidities (e.g. Demsetz, 1968; Tinic, 1972; Benston and Hagerman, 1974; Branch and Freed, 1977; Stoll, 1978; Stoll, 2000; Chordia et al., 2000). In the study of Demsetz (1968), he develops a theory of transaction cost and also first used economic analysis to prove that stock price is a determinant of bid-ask spread. Later, based on similar approach, Tinic and West (1972) further show that risk is also a determinant of spread. However, their study fails to include enough stocks in their sample while their measure for risk using high

[3] It seems surprising that the daily trading volume of every stock is always positive (also see Table 9 in Section 5). This phenomenon may be caused by the special investor segment in the Chinese stock market as the Chinese stock market is dominated by retail investors (explained in Section 3.5).

minus low over the average price is not a standard measure of risk. Benston and Hagerman (1974) then expand the sample size and improve the measure of risk and, they find that stock's unsystematic risk could affect the spread. In addition, using number of shareholders as a proxy for the trading scale, they also find it negatively affect the spread. Amihud, Mendelson and Uno (1999) utilize the special trading regulations in Japan and find that decrease in minimum trading unit could increase the number of shareholders, which is a proxy for trading scale, and finally lead to improvement in liquidity. Branch and Freed (1977) use data from American Stock Exchange (AMEX), a market that had not been investigated in literature yet and argue that trading activity like price, volume and volatility are determinants of spreads. Stoll (1978) then use data from NASDAQ and proves empirically that bid-ask spread is negative related to price while positively related to stock's risk, measured by volatility. Later, studies of Stoll (2000) and Chordia et al. (2000) extended the early studies by including other liquidity measures, larger sample size, and longer sample span and both studies find some consistent evidence that trading activity variables such as stock prices, volatility and trading volume, are correlated to liquidity. More specifically, Stoll (2000) find that a stock's relative quoted spread is negatively related to its volume and price while positively related to the stock's volatility. On the other hand, the number of trades affected spreads positively in NYSE/AMSE while it had negative impact on spreads in NASDAQ. Chai, Faff and Gharghori (2010) use six different monthly low-frequency liquidity measures including spreads, turnover, Amihud's Illiquidity ratio and zero return and zero trading measures in Australia stock market and suggested that trading activity characteristics are determinants of liquidities. When investigating the driven cause of movements in liquidities, Karolyi et, al. (2012) used cross-sectional test and time-series test and found that consistent with literature, market volatility and trading activities do impact the liquidities in different countries through 15 years periods.

Apart from trading activity variables, some researchers argued that firm's characteristics like market value and ownership structure will affect stock liquidity. In order to explain the small firm effect, Stoll and Whaley (1983) found that transaction cost could partly explain why small firms had abnormally high risk-adjusted returns. It is found that the proportional bid-ask spread for small-sized firms were larger than that for large-sized firms. Stoll (2000) compares the NYSE/AMSE to Nasdaq and found that firm size was positively related to the spreads in NYSE/AMSE while negatively associated to spreads in Nasdaq. Moreover, the ownership structure is also considered as a determinant of liquidity (Bolton and Von Thadden, 1998; Kamara et, al., 2008; Koch, et, al., 2009). When the ownership is concentrated, the shares that available for trading is constrained, thus leaving less trading activities and decrease in stock's liquidities. Moreover, higher concentration in ownership implies greater possibility of informed trading, which lead to decrease in liquidity. In the work of Heflin and Shaw (2000), by investigating the influence of block ownership on stock's market liquidity, they find higher block ownership (both managers' and other investors') would cause lower liquidity. Similarly, other researchers also find evidences support that higher block ownership would hinder firm's stock liquidity (Brockman et al., 2009). Jacoby and Zheng (2010) extend the work of Heflin and Shaw (2000) by including larger sample from Nasdaq and introducing new proxy for ownership dispersion. They also find that firm size played a significant role in the relationship between market quoted depth and changes in block shareholding of Nasdaq stocks. Lee and Chung (2018) analyse data from 20 emerging markets and find spreads decrease with foreign ownership. As the ownership disperses, the stock's liquidity improves. In contrast, Chu, Liu and Tian (2015) argue that divergence in ownership has detrimental effect on liquidity when investigate the Chinese market. Rubin (2007) finds a mixed impact that the level of institutional investors would improve the liquidity while the concentration of institutional investors would negatively influence the liquidity. Jiang, Kim and Zhou (2011) find that higher institutional ownership leads to lower spreads and price impacts, implying a higher liquidity.

Besides, the firm's corporate governance is proved to influence the stock's liquidity. Chung, Elder and Kim (2010) suggest that better corporate governance contributes to lower transaction cost and smaller price impacts, thus leading to improved market liquidity. Ali, Liu and Su (2017) find consistent evidence that firms with better corporate governance, which is measured using corporate governance quality, have lower trading cost and price impacts. When a firm has better corporate governance, the possibility of informed trading and effect of adverse selection are likely to be lower, thus lead to a higher liquidity.

From the market aspect, the trading venues and different trading mechanism are proved to affect liquidities. In early studies, researcher Benston and Hagerman (1974), Branch and Freed (1977), and Grossman and Miller (1988) propose an equilibrium model and argue that number of market makers and their immediacy to adjust to equate the supply and demand would directly influent the market liquidity. Atkin and Dyl (1997) even compare the trading volume between NASDAQ and NYSE, the former on is a dealer market and the latter is an auction market. They find a decrease in trading volume when stocks switch the trading venue from NASDAQ to NYSE. The studies mentioned all focus on the U.S. market (NYSE, AMEX and Nasdaq), which are quoted-driven market. Different from the U.S. market, stock markets in China and Australia are order-driven markets with no market markers. As Chai, Faff and Gharghori (2010) suggested, since there is no market maker and it is in fact public limit orders provide liquidity and establish the bid and ask prices, the market characteristics provide more transparent trading environment to market participants. Brown and Zhang (1997) compare a dealer market with a limit-order market and argue that information efficiency will be improved in order market. Malinova and Park (2013) compared order-driven market and quote-driven market and suggest that order-driven market has higher trading volume, which attracts more investors. Trading status like trading halts could have impact on liquidity.

2.3 Impacts of Margin-trading

Margin-trading is one type of leverage trading that investors borrow money from security companies to buy stocks. The margin rate, or sometimes called margin level, will definitely influence stock's price, liquidity, and volatility. If a stock's margin level sets at m%, an investor can borrow up to (100 – m) % from security companies when purchasing stock, with the purchased stock serving as collateral for the loan (Alexander et al., 2004). Most earlier literature just focuses on the impact of margin level. Largay III (1973) focuses on the special 100% margin requirement in U.S. during 1968-69 and investigates the impact of high margin restrictions on stocks' prices and trading volumes. He finds the prices and trading volumes of stocks under high margin restrictions decrease after the restrictions were posed. Hardouvelis (1990) examines the effect of raising margin requirements in the U.S. market from 1934 to 1987 and find that raising margin requirements can contribute to lower volatility in prices and smaller deviations from fundamental values. He argues that margin requirements can be regarded as effective policy tools to help stabilize the market and depress speculations. Hardouvelis and Peristiani (1992) investigate the effect of margin requirements in Japan and find that an increase in margin requirement can lead to a decrease in trading volume and a drop in trading activities from margin-buyers. Consistent with Hardouvelis (1990), they also believe that margin requirement can be an effective way to stabilize the market. Hardouvelis and Theodossious (2002) find asymmetry effects of margin requirement under different market condition. An increase in margin requirement is associated with lower volatility during bull and normal markets, but no such relation is found in bear market. In contrast, Seguin (1990) find that margin-trading does not harm the market as some regulators assumed, instead, introduction of margin-trading improves the market depth and lowers the volatility but increase the trading volume. Using data from 1993 to 1998 in the U.S. market and control market-wide factors that are not included in the study of Hardouvelis and Theodossious (2002), Alexander et al. (2004) also find an increase in trading volume after stocks were eligible for margin-trading. However, they fail to find any improvements in spreads or market depth when stocks become eligible for margin-trading. Using data from the Chinese stock market, researchers find improvements in price efficiency and decrease in volatility after lifting bans on margin-trading (Chang et al., 2014; Chen et al., 2016). More recently, Kahraman and Tookes (2017) find that an improvement liquidity after a stock becomes eligible for margin-trading in the Indian stock market. They also prove that the positive effect of margin-trading on liquidity is caused by margin traders' contrarian strategies.

Apart from the impact of margin requirement and eligibility, margin-trading will impact the stock's liquidity through deleveraging. According to the model of Brunnermeier and Pedersen (2009), it predicts that margin-trading can be destabilizing as it can increase the illiquidity of stocks after a drop in stocks' prices. The stock's market liquidity and investor's funding liquidity are mutually reinforcing, leading to "liquidity spirals" in a market crash period. More specifically, when an investor margin purchases a stock, a decrease in the stock's price will cause a decrease in collateral's value, and lead to a margin call, which decreases the investor's funding liquidity. If the investor is facing a funding constrain and fails to meet the margin requirement, then he has to force liquidate the margin purchased stock, which will decrease the price and liquidity of the stock. Therefore, margin-trading activity can impact the stock's liquidity and investors' funding liquidity. Kahraman and Tookes (2017) prove this theory as they find margin-trading's impact on liquidity become negative during the market crash period.

In addition, some researchers argue that margin-traders are informed traders while others hold the opposite opinion. For example, Alexander et al. (2004) find margin level is positively related to adverse selection components of the spread, which suggests that margin-traders are more likely to be informed traders. Hirose, Kato and Bremer (2009) find similar results using weekly margin-trading data in Japan. Their findings suggest that margin-traders have herding behaviors while margin-trading could predict future returns in the Japanese stock market. In contrast, Chang et al. (2014) fail to find any return predictive power in margin-trading, implying that margin-traders are probably not informed traders.

2.4 Impacts of Short-selling

2.4.1 Impact on Price and Return

Short-sales have different purposes. In the common view, investors, especially the speculators, use short-sales to make profit by shorting stocks at higher prices then return them at lower prices. Therefore, public believe that short-sellers may deliberately drag down stock prices by selling at aggressively low prices or even spreading rumors about the firm or the whole market to decrease share values. Goldstein and Guembel (2008) even prove that in theory, short-sellers can manipulate price using “bear raid” strategy. It is these trading that attract public’s attention to blame market crash on short-sellers. However, short-sales can serve for other functions. For example, for brokers and dealers, short-selling is an approach to fulfill the market-making function while for institutional investors, it is an essential hedging strategy. Short-sellers can enhance the market’s integration by disclosing information about over-valued stocks and correct the stock prices to the fundamental value (Akabas et al., 2008; Boehme et al., 2006; Boehmer et al., 2008).

As a trading mechanism to fulfill the integration of market, short-sale is argued to have influence on stock prices. Lintner (1971) argues that according to CAPM with homogenous invertors beliefs, short-selling should only have hedging purpose, so short sale constraints would have no impact on price. Diamond and Verrecchia (1987) argue that if investors have rational expectation, then short-sale constraints will not influence the stock price to deviate from its fundamental. However, if investors are less than fully rational and are heterogeneity, short-sale constraint does affect the price (Harrison and Kreps, 1978; Duffie, 1996; Duffie et al., 2002). In contrast to the opinion that short-sale constraints will not influence the stock's price, according to Miller's (1977) seminal model, short-sale constraints would lead to stock overpricing, since the pessimistic investors who do not originally own the stock are sidelined from trading. Jarrow (1980) compares two identical markets that the only difference is short sale constraints. Using the single period mean-variance model, he predicts that under heterogeneous expectations, price can be either upward or downward, depend on parameter of economy. However, if investors have homogenous expectations of the covariance matrix of future prices, short sale constraints will increase risky asset's prices, which is consistent with Miller's (1977) prediction. Shleifer and Vishny's (1997) model predicts that stocks will become overpriced caused by market imperfections and limits to arbitrage if short-sale is restricted. Also, Chen et al. (2002) suggest that short-sale constraints tend to inflate prices. Liu and Wang (2013) find that bid price with short-sale constraints is lower and ask price is higher than that without short-sale constraints using an equilibrium model.

Though theoretical models have divergences in the impact of short-sale bans on the stock's prices, the empirical evidence prone to support that short-sellers are more well-informed and trade to prevent prices from being overvalued so bans on short-selling will inflate the stocks' prices (Chen et al., 2002; Chang et al., 2007; Lamont, 2012). For example, Chang et al. (2007) take advantage of short-selling pilot trail in Hong Kong where only specific stocks are designated to lift the bans on short-selling to investigate the price change after lifting bans. They find both price effects and negative event returns on stocks eligible for short-selling after bans were lifted. The overvaluation in the eligible stocks' prices is caused by short-sale constraints, which is consistent with Miller's (1977) overpricing prediction. Sharif, Anderson and Marshall (2014) also find similar result which support Miller's (1977) model as they find that differences between prices of stocks that eligible and ineligible for short-selling become smaller after bans on short-selling were removed.

Short-sales can influence the prices when it is costly to short, in that case, stocks can also get overvalued. By reviewing short-selling bans during the 1930s crisis, Jones (2012) finds that policies from regulators made shorting to be more difficult. During 1920s and 1930s, stocks that were expensive to short had higher prices and abnormally low returns in the future (Jones and Lamont, 2002). Duffie, Galeanu and Pedersen (2002) construct a model and consider the impact of lending fees as high lending fee will bid up stock prices. Lamont and Thaler (2003) find that even though bubbles in the technology sector exist and stocks related are so overpriced that arbitrage should have been possible, the high cost on shot-sales made short positions difficult to establish. Therefore, the stocks' prices remain at overpriced level and cannot be adjusted to fundamental values. However, Diether et al. (2009) fail to find supporting evidence that bans on short-sales influence stock prices. There is no change in share prices when Regulation SHO's pilot program restricted short-selling.

According to Miller's (1977) model, short sale constraints prevent opinion of pessimists, which cause the overvaluation of stock prices and will lead to low future returns. To test Miller (1977), researchers focus on relationship between difference of investors options and stock return. Consistent with Miller (1977), Diether, Malloy and Scherbina (2002) use dispersion of analyst's earnings forecasts to measure degree of divergence in opinions. They find that higher the divergence, lower future return. Similarly, Boehme, Danielsen and Sorescu (2006) find that high dispersion and short-sale constraints are both required to induce overvaluation. Furthermore, Boehmer et al. (2008) find that short sellers can gain higher excess returns. Diether et al. (2009) discover that short-selling trading volume increase more following price increases and positive returns. They find out that short sellers can positively predict future returns over a five-day horizon, suggesting short sellers may have access to some insider information, especially negative one. Supporting this explanation, Karpoff and Lou (2010) find that short-selling activity increased before a financial misconduct while Desai et al. (2002) and Asquith et al. (2005) find that short interest and future returns are negatively correlated. Short sales have predictive power on future returns, implying short sellers are informed traders. Finding from Desai et al. (2006) that short sellers can anticipate earnings restatements before they are announced publicly further support the hypothesis that short-sellers are likely to be informed traders. Christophe et al. (2004) also find abnormal higher short selling before negative earnings surprises and Boehmer et al. (2015) find similar heavy increase in shorting during the week before analyst downgrade recommendation or negative forecast revisions. Chang et al. (2014) investigate the pilot scheme in Chinese stock market that certain stocks on a list are eligible for short-selling. They find consistent evidence that short-selling activity can predict future returns.

Another explanation for the prediction power in future returns by short-sellers is that short-sellers tend to be sophisticated investors so they can identify overpriced stocks better than other investors (Diether et al., 2009). For example, Boehmer et al. (2008) conclude that 74% of short-selling orders are executed by institutional investors and very few are executed by individual investors. Short-sellers sometimes use certain indicators to capture overvalued stocks that they target firms with high P/E ratio and M/B ratio (Dechow et al., 2001).

2.4.2 Impact on Price Adjustment and Price Efficiency

Diamond and Verrecchia (1987) predict that with short-sale constraints, price will adjust more slowly to negative information because short-sale constraints prevent informed investors to trade on negative news. Emprically, Bris et al. (2007) find supporting evidence from an international comparison using different market efficiency measures. They conclude that downward price moves are slower in markets where shorting is prohibited while in countries where short sellings are allowed, price incorporate with negative information more efficiently. Using data from 26 countries, Saffi and Sigurdsson (2011) find lower efficiency for stocks in countries with more stringent short-sale constraints. Beber and Pagano (2013) use data on different short-sale bans from international stock market during the 2007-09 financial crisis and also find short-sale bans hampered price discovery.

Researchers also argued about the impact of short-sale constraints on the stability of the market. For regulators, they believe that bans on shorting can stabilize the market in the financial crisis time (Jones, 2012). Xu (2007) develops an investors' perspective model and also predicts increasing skewness under short-sale constraint, supporting the idea that short-sale constraints lead to more stable market. Empirically, Bris et al (2007) find in countries where short-selling is not allowed, stock returns are less negatively skewed. When short-sale bans are lifted in Hong Kong, volatility increases and the possibility that extremely negative returns occur also increases

(Chang et al., 2007).

However, other researchers have opposite views toward the impact of short-sale bans. Diamond and Verrecchia's (1987) model predicts more negatively skewed returns under short-sale constraint since prices are adjusted slower to negative information. Hong and Stein (2003) construct a model, suggesting that investors with negative information are prevented from trading until the market drops when accumulated negative information comes out, which destabilized the market and exacerbate the crash. Boehmer et al. (2013) find that the short-sale ban in US, which was intended to stabilize the turbulent stock market, fails to increase the prices and the ban has other side-effects of reducing liquidity, slowing down price discovery and impending market-making for options. When constraints are removed or relaxed, there are no increases in volatility and occurrences of negative returns (Saffi and Sigurdsson, 2011).

2.4.3 Impact on Liquidity

The impacts of short-selling constrains on liquidity are mixed. Based on Glosten-Milgrom (1985) model, Diamond and Verrecchia (1987) conclude that short sell constrains can reduce the price discovery speed because of preventing informed investors to trade on negative news. This would further increase the bid-ask spread. However, this model is based on a homogeneous assumption that the constraints influence investors equally, whether informed or not (the market makers are risk neutral and make zero expected profit for each trade). If investors are not influenced at the same level, the impact of short-sale constraints on liquidity would be unclear. Liu and Wang (2013) develop an equilibrium model and propose that short-sale constraints will increase the spread and decrease market depth, thus hinder the liquidity. Empirical studies tend to support Liu and Wang's (2013) prediction. Boehmer et al. (2013) find that bans on short-sale in US reduce liquidity and Beber and Pagano (2013) also find short-sale constraints imposed during 2007-09 financial crisis around the world increase the bid-ask spread thus lower the liquidity. Charoenrook and Daouk (2009) compare the data from 111 countries and argue that stocks that eligible for short-selling tend to have higher liquidity. Thus, banning short-sale cannot contribute to stabilize the market. Alves, Mendes and da Silva (2016) find consistent evidence in European markets that short-sale bans have detrimental impact on liquidity. The similar result stands in Australian market as Helmes et al. (2017) find that short-sale constraints will increase the bid-ask spread when examining the impact of short-sale bans in Australian stock market during the financial crisis period. Li et al. (2018) contend that short-selling activities could contribute to improvements in liquidity in the Chinese stock market, as they provide additional liquidity to the market. On the contrary, Sharif et al. (2014) also focus on the Chinese market and argue that short-selling decrease the liquidity as stocks that eligible for short-selling tend to have higher spreads. Their finding is consistent with Ausubel's (1990) theory that uninformed traders just avoid the short-selling eligible stocks to avoid trading with informed investors. In addition, study of Cai et al. (2013) also support Ausubel's (1990) theory as the empirical results suggest that stocks that are eligible for short-selling have lower liquidities. They argue that this detrimental effect of short-selling is caused by adverse selection. Short-sellers, as informed traders, just deter uninformed traders from trading the short-eligible stocks. Instead, uninformed traders switch their trading to other short-ineligible stocks, thus lead to the decrease in liquidities of eligible stocks.

CHAPTER 3: INSTITUTIONAL SETTING

3.1 Margin-trading and short-selling development in China

At the end of June 2006, the China Securities Regulatory Commission (CSRC) released "Measures for the Administration of Margin Financing and Securities Lending Services of Securities Firms on Trial Basis" which began the process of preparing the relevant parties (e.g., securities firms, stock exchanges, and investors) in the Chinese stock market for margin-trading and short-selling. The chairman of the CSRC Fulin Shang believed that the introduction of margin-trading and short-selling could encourage the innovation of the stock market while stimulate the trading activities.[4] During the period between June 2006 and March 2010, when margining trading restrictions were lifted on a trial basis, the CSRC and stock exchanges released several relevant legislation and detailed rules (see **Table 1**). According to a CSRC officer, the trial program would not begin until the CSRC believes that China's legislative framework has been refined for margin trading activities and when the global capital markets have recovered from the 2008 financial crisis. After 21 months from December 2011, the CSRC announced the trial program's successful completion and officially lifted the margin-trading restrictions.

3.2 Qualification of Stocks and Investors for Leveraged Trading

The dates of lifting bans on margin-trading and short-selling are collected manually on the websites of CSRE, SSE, and SZSE (see **Table 2**). The first date that bans were lifted is 31st March, 90 stocks with large market capitalization and high

[4] http://www.csrc.gov.cn/pub/newsite/hdjl/zxft/lsonlyft/200710/t20071021_95204.html

Table 1. Policy History of Margin-trading and Short-selling Trial

Date	Legislations, rules, and events	Releasing bodies
30th June 2006	Measures for the Administration of Margin Financing and Securities Lending Services of Securities Firms on Trial Basis	CSRC
21st August 2006	Detailed Rules for the Implementation of Margin Financing and Securities Lending Transactions	SZSE and SSE
29th August 2006	Rules for the Implementation of Registration and Clearing Services for Pilot Margin Financing and Securities Lending Services for China Securities Depository and Clearing Limited Company	China Securities Depository and Clearing Corporation (CSDC)
5th September 2006	The essential clauses of the contract for margin financing and securities lending & The essential clauses of the risk disclosure statements of margin financing and securities lending	Security Association of China (SAC)
8th April 2008	Measures for the Risk Control Indexes of Securities Companies Notice of problems emerged from further regulating security companies' divisions (Draft) Provisions on the Regulation of Branches of Securities Companies (for Trial) Open to the public consultation	CSRC
25th April 2008	Regulation on the Supervision and Administration of Securities Companies Regulation on risk management of security companies	State Council
5th October 2008	Trial of Margin Trading and Short Selling Began[5]	CSRC
31st October 2008	Announcement No. 42 [2008] of China Securities Regulatory Commission: Interim Provisions on the Examination and Approval of the Business Scope of Securities Companies	CSRC
8th January 2010	Fundamentally agreed with pilot margin trading and short selling	State Council
30th April 2010	Announced pilot project of margin trading and short selling officially started	SZSE and SSE

liquidity from Shanghai Stock Exchange (SSE) and ShenZhen Stock Exchange (SZSE) were selected as the pilot stocks for margin trading activities. In December 2011, when the margin trading constraints were officially lifted, the number of stocks eligible for

margin trading increased to 278. Since then, the list was expanded several times. With the development of margin-trading and short-selling, more stocks are included in the list that allowed for margin-trading and short-selling. The last inception date is 21st October, 2019 and 43.6% (1600/3671) of stocks are eligible for margin-trading

[5] http://www.csrc.gov.cn/pub/newsite/zjhxwfb/xwdd/200810/t20081005_68632.html

Table 2. Number of Stocks that is Eligible for Margin-trading and Short-selling[6]

Event No.	**Effective Date (Inception Date)**	Number of Shares Added	Number of Shares Removed	Total Number Accumulated
1st	2010.3.31	90	-	90
2nd	2011.12.5	191	3	278
3rd	2013.1.31	276	54	500
4th	2013.9.16	206	6	700
5th	2014.9.22	218	18	900
6th	2016.12.12	77	27	950
7th	2019.10.21	711	61	1600

This table shows the major changes in the list of stocks that are eligible for margin-trading and short-selling. Only 90 stocks were eligible for margin-trading and short-selling at first.

and short-selling at that time.

Table 2 displays the number of that are eligible for margin trading since March 2010. In fact, eligible stocks that listed in SSE are component stocks for Shanghai Stock Exchange Index (SSE Index). For example, the first 50 stocks that allowed for margin-trading and short-selling are the components of SSE Index 50, while in 2011, all the eligible stocks come from SSE Index 180. From 2013, the CSRC specifically announced the requirements for the stocks that are eligible for margin-trading and short-selling should be those that qualified the following criteria:

1. Stocks have to be listed and traded in the Stock Exchange for at least three months;

2. Stocks that eligible for margin-trading should have at least 1,000 million number of shares outstanding or with the least market capitalization of 5,000 million;

3. Stocks that allowed for short-selling should meet the minimum requirement

[6] Notice:
(1) Stocks are eligible for both margin trading and short selling simultaneously;
(2) Some stocks became disqualified during time (e.g. market value lower than the requirement), then the stock exchange would remove the stock from the eligible list and publish announcement of removal on the stock exchange website;
(3) This thesis only focus on the first six events, the last ban-lifting event occurred in 2019 is not included in the sample period.

for 2,000 million number of shares or 8,000 million RMB of market value;

4. Number of shareholders should over 4,000;

5. The following situations did not happen over the past three months: i) the stock's daily turnover is less than 15% of the index benchmark turnover with a trading volume of less than 50 million RMB; ii) the stock's daily return deviates from the index benchmark return for more than 4%; iii) the stock's volatility is five more times than the index benchmark volatility;

6. Firms that issue the stocks should have finished the Full Circulation Reform for Listed Companies;

7. Stocks are not among the special treated (ST) group.

Following these requirements, only stocks that are relatively large and involatile can be included as those eligible for margin-trading and short-selling, implying the government's attempt to avoid any potential sharp volatility or manipulation of prices on smaller and unstable stocks. In March 2015, the CSRC announced that to boost the short-selling trading activity in the Chinese stock market, more stocks, estimated at least 500, will be included in the list that allowed for short-selling. However, only a few months later, this plan for boosting short-selling aborted when the Chinese stock market faced the most massive market crash in July 2015. Both the regulators and investors believe that short-selling could aggravate the market crash.

Based on the principle of prudence, the CSRC had required that only investors with sufficient experience in security investment and risk-bearing capability could invest in stocks with margins. The securities firms (i.e., brokers) will have to select their margin trading clients based on this principle. The more explicit criteria for the qualified investors are not specified in the released file but through moral suasion.

The guidance opinion is that to open the margin trading account with a broker, an individual investor has to have financial assets worthy of at least 500,000 RMB and had opened his/her regular trading account with the broker for at least 18 months.[7]This guidance opinion put a high threshold where only experienced investors with sufficient financial assets can be involved in margin-trading and short-selling activities.

In its revised version of the document[8], the CSRC specifies that margin trading should not be made available to the investors who lack the risk-bearing capability, who have material fraud records, or who have opened the regular trading accounts with their brokers for less than six months. In April 2013, the CSRC announced that the brokering firms could decide the thresholds for new margin trading accounts based on the suitability doctrine.[9] In order to compete for the margin trading business, soon after this announcement, many security companies lowered the financial threshold for eligible investors significantly. For example, GuoTaiJunAn (GTJA), a reputed broker in China, only required its customers to have more than 100,000RMB of financial assets to qualify for the margin trading account. The loosened criteria for margin trading accounts have caused the number of margin trading accounts opened in various brokers to increase exponentially since then.

Accordingly, standards of eligible investors continued to decline. By the end of 2014, all of the brokers have only required investors with six months of account activity to open the margin trading account, and the financial threshold was becoming lower. One extreme case was HuaTai Security Company even reduced the

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7 http://stock.hexun.com/2010-01-23/122462185.html

8 i.e., *Measures for the Administration of Margin Financing and Securities Lending Services of Securities Firms on Trial Basis*

9 http://finance.sina.com.cn/stock/quanshang/qsyj/20130426/162715294894.shtml

capital requirement to zero. These inappropriate behaviors of some of the brokers have finally alerted the CSRC. At the beginning of 2015, the CSRC rectified this situation by stressing the congruence in both time and capital requirements for investor eligibility. Consequently, the proposed guidance opinion has pulled the financial threshold for the margin-trading account back to 500,000RMB.[10]

3.3 Margin Requirements and Collateral Discounts

Although individual security companies have autonomously imposed heterogeneous margin requirements on various stocks, they need to comply with requirements settled by Stock Exchanges[11]. According to such regulations, the margin rate, defined as the proportion of margin value to the total value of margin financing/short selling, should be at least 50%. Both cash and securities can be used as collaterals, and there was no compulsory requirement on the proportion of cash as margin. However, as securities' values fluctuate over time under diverse risk levels of securities, the discount rates for these securities also varied (illustrated in the following section). The requirements also settled the least margin maintenance ratio at 130%. Unlike the margin ratio, this margin maintenance ratio is the ratio of asset (both self-owned and borrowed from the broker) value in the account to the borrowed asset's value. Mathematically, it is

$$\text{margin maintenance ratio} = \frac{cash + market\ value\ of\ securities\ in\ the\ credit\ account}{capital\ and\ securities\ borrowed\ via\ margin\ trading\ and\ short\ selling + loan\ fees}$$

$$= \frac{asset\ owned + asset\ borrowed\ using\ margin\ trading\ and\ short\ selling}{asset\ borrowed\ using\ margin\ trading\ and\ short\ selling}$$

10 http://stock.hexun.com/2015-01-20/172567513.html

11 According to *Shanghai/Shenzhen Stock Exchange on Issuing Detailed Rules for the Implementation of Margin Trading and short selling*

If the account's margin maintenance ratio is below this lowest requirement 130%, investors will receive a margin call, a request for additional margin. The margin balance will be re-calculated on a daily basis; if one investor fails to fulfill the required margin (i.e., keep margin maintenance ratio higher than 150%) within two days after the margin call, the broker can force close the positions. However, this margin maintenance requirement is canceled in July 2015, right after the market crash to relieve investors' severe potential loss if positions are forced closed. Brokers could set the margin maintenance ratio by themselves instead of strictly following the 130% requirement. As a result, they tend to lower the ratio and prone to not force close the positions of investors.[12]

Margin can either be cash or securities. However, if securities are used as collaterals, their values should be discounted since their market values could fluctuate. Therefore, the discount rates are related to the risk levels of securities. As clearly stated by ShangHai Stock Exchange (SSE) and ShenZhen Stock Exchange (SZSE), different types of securities have their highest discount rates, and the guideline discount rates are showed in **Table 3**.

Different security companies sometimes claimed independent discount rates for the same security, and the discount rate also varied with time according to the risk of securities. Later in 2016, the CSRC modified the discount rates requirements. According to the updated requirement, the discount rate should be zero for stocks with static Price/Earnings (PE) Ratios higher than 300 or negative since these stocks are considered as high risk level stocks.

[12] http://www.csrc.gov.cn/pub/newsite/zjhxwfb/xwdd/201507/t20150701_280174.html

Table 3. Discount Rates Requirements from SSE and SZSE

Security Type	SSE	SZSE
Warrant	0	0
Corporate Bond	0.8	0.8
Government Bond	0.95	0.95
Listed Funds	0.8	0.8
ETF	0.9	0.9
Special Treated A Shares	0	0
Shares not included in SH Index180/SZ Index100	0.65	0.65
Component shares in SH Index180/SZ Index100	0.7	0.7

3.4 Margin Interest Fee

Both margin-trading and short-selling have their loan interest rates, determined by individual security companies. In 2010 when the given practice started in China, six security companies, the first bunch of authorized service suppliers, regulated their loan interest fees. They based interest rates on the benchmark interest rate for half-year loan published by the People's Bank of China (PBoC) and rose by 3 percent, for both margin-trading and short-selling. For example, the half-year loan on 31st April 2010 was 4.86%, the interest rate for margin financing and securities lending was 7.86%. Later in November, these security companies increased interest rates to 8.10% as the PBoC rose the benchmark interest rate. As more security companies participated in the market, the offered interest rates became diversified yet still closely related to the benchmark interest rate. Some security companies just had the same rate for both margin financing and securities lending. For example, the loan fees for margin trading and short selling were both 8.35% in April 2015 for

GuoTaiJunAn, ZhongXin, HaiTong; However, for BoHai, it was 8.35% for margin trading and 10.35% for short selling[13].

Both margin-trading and short-selling behaviour are not complete and mature in China. According to Measures for the Administration of Pilot Securities Lending and Borrowing Business of Securities Companies, security companies can only loan their own capital and stocks to investors. Despite reduced risks, such a regulation generated some drawbacks. First, limiting the resources to what security companies have may refrain the development of margin-trading and short-selling since sometimes investors cannot borrow enough capital or stocks as they expected. In addition, security companies may prefer to maximize profit through their existing resources rather than lend them to customers for interest since the profit may probably overweight interest when investment opportunities emerge.

In April 2008, in Regulation on the Supervision and Administration of Securities Companies approved by the State Council, refinancing was first proposed to solve these problems. Later in October 2011, CSRC published Pilot Measures for Supervision and Administration of Refinancing Business in which refinancing business was officially allowed. According to these regulations, refinancing is a mechanism where security companies that are short of capital or stocks are allowed to acquire resources from professional financial institutions such as bank, fund, insurance company or special security finance companies. In many foreign markets like U.S., refinancing is commonly used and is open to the market. Security companies can freely choose banks or funds to raise capital and stocks. However, in China, security companies can only refinance via one channel: the special security finance company founded by the government. China Security Finance (CSF)

[13] GuoTaiJunAn, ZhongXin, HaiTong and BoHai are main security companies in China.

Corporation is the only institution that provides margin financing loan services to qualified security companies in China.

In August 2012, refinancing for margin trading was officially approved and later in February 2012, refinancing for short selling was allowed. The introduction of refinancing improved China's stock transactions system and enhances the completeness the market's functions.

3.5 Investors Segments and Specific Trading Rules

The investors that dominate the stock markets in China are mainly the individual investors while institutional investors dominate the stock markets in many developed countries like U.S. and UK (Lee et al., 2010). According to the 2018 Annual Statistics from the Shanghai Stock Exchange (SSE), over 99% of investors in the market are retail investors (or called individual investors) and their trading activities account for 82.01% of the total market trading activities. In contrast, the institutional investors only accounts for less than 20% of the total market trading activities, which seems to be abnormal in the U.S. or U.K. stock markets. Because of the high participation of retail investors, trading in the Chinese stock market are highly active that the trading volume for every stock could never be zero unless the case of trading halt. More interestingly, though the individual investors dominate the stock market, their profit abilities are relatively low comparing to institutional investors. This investors segmentation could partly explain the reason why margin-trading dominates the market. Individual investors are not as sophisticated as the institutional investors; thus they are not familiar with short-selling as institutional investors. They could rather follow the traditional trading pattern which buys at a lower price and sells at a higher price to obtain profit.

As a relatively new stock market which established three decades ago, the Chinese stock market has several specific trading rules that designed to protect investors. One special trading regulation is called “T+1”. According to this rule, investors in the stock market cannot trade the stocks on the same day of transaction. However, investors could trade immediately in the option markets since there is no such regulation in financial derivative markets in China. Moreover, when investors use leverage trading, they could also margin buy or short sell on the same day of transaction.[14]Another special trading regulation is "Price Limit". According to the trading regulation of the Chinese stock market, a stock's price can only move by 10%, either up or down, compared to its closing price from last trading day. The regulator believes that this limit in price movement could partly protect investors and stabilize the market from volatile price movements. The third special feature is the trading status. The stock exchange would determine whether a stock is subject to "Special Treatment" according to the underlying firm's accounting performance. Sometimes, when a company faces some problems (e.g. high probability of bankrupt, high leverage, continuous deficits) that would lead the stock exchanges to believe there is high probability of bankruptcy, its stock would have a trading status as special trading (ST) status. These special trading (ST) stocks would have many restrictions in trading like only 5% price limits. Therefore, ST stocks are believed to be of highly risk. This trading status is actually a warning sign given to the investors. Any ST stocks are not eligible for margin-trading nor short-selling.

[14] During the market crash period (July 2015), margin-trading and short-selling still need to follow this “T+1” trading rule.

3.6 Policy Changes after the Market Crash

Since both margin-trading and short-selling businesses are relatively new in the Chinese stock market, the regulators impose several specific restrictions on these activities. First, naked short-sale is prohibited in China that investors cannot short stocks unless they do borrow shares from the brokers. In addition, both margin-borrowing and short-selling have a duration of 180 days (or 6 months). According to the Measures for the Administration of the Margin Trading and Short Selling Business of Securities Companies, investors need to finish the position before the period of 180 days and any trading that exceed the time limit would be penalized or even forced the position. For stocks that eligible for margin-trading and short-selling, the stock exchanges can suspend the trading behavior when the amount of shares that be margin-financed or short-sold is larger than 25% of its total market capitalization until that drops to 20%.

The market crash happened during the middle of June 2015. On June 15th, the Shanghai Composite Index dropped by 2% and the next day the market index continued decreasing by 3.47%. The most severe crash took place on date June 19th and June 26th, as the market index dropped by 6.42% and 7.4% respectively. On June 26th, more than two thousand stocks prices decreased by 10% and reached the price limits. To stabilize the market and encourage the investors' confidence, regulators imposed several policies while some are related to the margin-trading and short-selling activities.

On June 29th, the first trading day after the major market crash, the CSRC announced that there still be enough developing potential for margin-trading and also encourage brokers to expand the margin-trading activities. On the same day, the CSF corporation also responded to the public that very few forced liquidations took place in the market and investors should not be panic about either margin-trading or short-selling activities. On July 1st, the CSRC announced that channels for margin-financing would be broadened in the future as all security companies could use trading systems between security exchange and institutions to gain the capital for margin-trading. The CSRC also modified the Measures for the Administration of the Margin Trading and Short Selling Business of Securities Companies to allow extending the duration of margin-borrowing and short-selling from 180 days (half-year) to more days. Moreover, the margin-maintenance-ratio can be lower than 130% while security companies can determine the collateral and the relevant discount rates. In summary, these changes in policies aim to relax the regulation on margin-trading and short-selling activities and finally, reduce the possibility of forced liquidation. Later in the middle of July, SSE and SZSE advised security companies to cease the short-selling activity in order to stabilize the market. On August 3rd, the CSRC modified the Measure for Margin Trading and Short Selling again and prohibited the intra-day trading (generally written as T+0). Instead, investors for margin-trading and short-selling should wait one trading day to exercise the stocks borrowed/margined (usually called T+1). Right after this constraint on intra-day trading, the volume for short-selling dropped significantly.

3.6 Margin-trading and Short-selling Statistics

Shown in **Table 4** and **Table 5**, the number of investors engaged in margin-trading and short-selling surged after 2010, together with the increase in the trading volume. It seems that margin-trading and short-selling have been popular in

China and they have developed rapidly. However, compared with the whole market, margin-trading and short-selling only accounted for a part of trading. First, the stocks that allowed for margin-trading and short-selling account only part of the stocks in the whole market. At the end of 2016, totally 2831 stocks listed in the A-share market, only 33.56% (950/2831) of them are allowed for margin-trading and short-selling. This percentage is still lower compared to the U.S. market or European markets. Similarly, on the same day, margin-trading and short-selling only share less than 20% of the total trading volume. Such data may indicate that the market was not as mature and complete as that in developed countries like U.S. and it still has a large developing space for margin-trading and short-selling.

In **Table 6**, the summary statistics for margin-trading and short-selling activities are showed. The first panel shows the statistics for margin-trading purchase, recovering and related balance while the second reveals the statistics related to short-selling activities. These two panels imply that both activities developed rapidly over these years. However, margin trading is more than short selling as the volume, turnover and the balance for margin-trading activity are much higher than that for short-selling activity. Especially in 2015, the margin-trading activities reached a peak while short-selling activities decreased compared with previous years before the market crash.

Investors' preference for margin trading can be explained for several reasons. First, the time that short-selling is allowed is very short and investors are not familiar with this new trading mechanism. As a result, when they are introduced to margin-trading and short-selling, they tend to choose the activity with familiar trading mechanism, buy at a lower price and sell at a higher price. Moreover,

Table 4. Number of Margin-trading and Short-selling Accounts at the End of Each Year (2010 – 2016)

Time (End of year)	Number of accounts opened	Accumulated accounts
2010	42211	42083
2011	309421	348610
2012	638039	990284
2013	1690373	2671728
2014	3151713	5864300
2015	2021193	7896746
2016	609116	8446010

Table 5. Total Value of Margin-trading and Short-selling for Each Year (2010 - 2016)

Time	Value of shares margin purchased (billion RMB)	Value of shares short sold (billion RMB)	Total Trading Amount (billion RMB)
2010	70.09	1.28	71.37
2011	297.56	27.39	324.95
2012	725.58	177.89	903.47
2013	3293.56	579.49	3873.04
2014	9579.22	1126.78	10705.99
2015	32472.94	2923.33	35396.26
2016	11481.18	83.62	11564.80

short-selling is much riskier than margin-trading as it may cause unlimited losses theoretically (stock price could only drop to zero but increase to an unlimited level). More importantly, the supply of security that could be used for short-selling is limited than the supply of capital than could be used for margin-trading. Even though investors are willing to short sell stocks, the resources that they can access is very scarce. In an extreme case, the balance of short-selling is zero, implies a short-sell constraint. This could partly count for disproportional little increase in short-selling after the market crash even no bans imposed on short-selling behaviour.

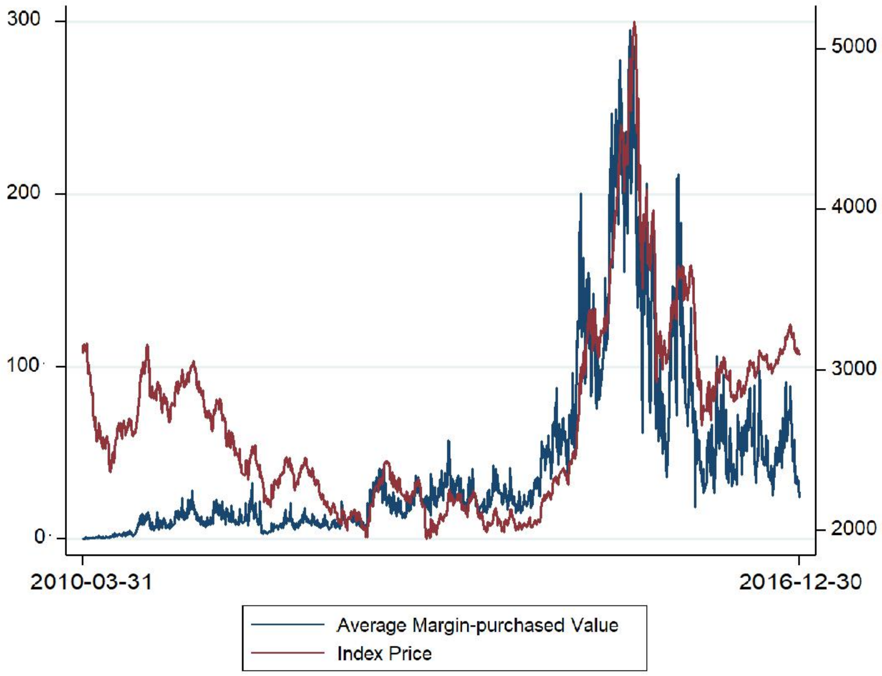
In **Figure 1**, the trends of margin-trading and short-selling with the Shanghai (Securities) Composite Index (SCI) price from 2010 to 2016 are plotted. From **Figure 1** Panel A, it is evident that the margin-trading activity was developing at relatively low speed from 2010 to 2014 as the number of stocks that eligible for margin trading only account for a small proportion of the total stocks. Until mid of 2014, the margin-trading began to boost as more stocks were allowed for margin-trading. The margin-trading activity then moves together with the index price. When the market is under good condition, margin purchases from investors also increase; while the market crashes, the margin-trading activity plummet with the market. In Panel B, the short-selling activity also began at a relatively low level as investors were not used to short-selling right after bans were lifted. When the market was under good condition, the short-selling activities also increased. However, when the market has an upward trend, the short-selling tend to have a downward trend, which is consistent with the intuition that short-sellers are less likely to gain profit in an upward trend market. However, after the market crashes in mid-2015, the value of shares being shorted plummeted to a low level. Though the regulators did not pose bans on short-selling, security companies were reluctant to lend stocks to investors, which made short-selling became difficult hereafter.

Table 6. Summary Statistics for Margin-Trading, Short-Selling and Related Balance

	2010	2011	2012	2013	2014	2015	2016
Average daily finance purchase volume	311,299	1,086,705	1,100,602	2,647,077	5,021,657	11,090,662	55,867,467
Average daily finance purchase turnover	0.7723%	4.5691%	7.5891%	13.5056%	20.0486%	20.5230%	19.5637%
Average daily finance repaying volume	250,532	986,006	1,027,800	2,434,593	4,674,015	11,142,807	56,626,849
Average daily finance repaying turnover	0.6116%	4.2149%	7.1815%	12.8286%	19.8099%	21.7023%	20.6914%
Average daily finance balance volume	3,898,253	25,629,098	23,917,284	42,677,311	65,264,898	109,975,000	965,312,960
Average daily short sell volume	4,531	86,574	194,137	373,895	474,555	852,983	301,654
Average daily short sell turnover	0.0136%	0.4287%	1.2698%	1.3718%	1.2220%	0.7306%	0.0837%
Average daily short repurchase volume	4,495	84,475	190,567	373,923	473,660	854,187	295,467
Average daily short repurchase turnover	0.0138%	0.4283%	1.2656%	1.3748%	1.2238%	0.7308%	0.0920%
Average daily short balance volume	10,577	184,296	415,511	556,036	371,021	221,839	171,177

Average daily finance purchase/ short sell volume is the cross-sectional average of the daily numbers of shares margin purchased/ sold short. Average daily finance repaying/ short repurchase volume is the cross-sectional average of the daily number of shares covering finance position/ short position. Average daily finance purchase/ repaying turnover is the proportion of finance purchase volume/ finance repaying volume to daily trading volume. Average daily short sell/ repurchase turnover is the proportion of short sell volume/ short repurchase volume to daily trading volume.

Figure 1. Margin-trading and Short-selling Compared to the Market Trend



Panel A: Daily average value of shares margin purchased and Daily Index Price

Panel B: Daily average value of shares short sold and Daily Index Price

The blue lines in Panel A and Panel B represent the daily average value of shares purchased on margin and the daily average value of shares being shorted. The red lines in panels A and B show the price of Shanghai Security Composite Index (SCI). The period is from March 31, 2010 to the end of 2016. The left vertical axes in Panel A and Panel B are the value of shares being margin purchased and short sold, in million RMB. The right vertical axes in Panel A and Panel B are the prices of SCI.

CHAPTER 4: DATA DESCRIPTION

4.1 Data Sources

My sample includes all A-share stocks listed on different boards[15] of Shanghai Stock Exchange (SSE) and ShenZhen Stock Exchange (SZSE). We collect all the available trading data over the period from March 31st, 2010, to December 31st, 2016. Our data consist of daily trading activities, margin-trading and short-selling ban characteristics, margin finance and short sell balances, ban-lifting dates and bid and ask prices for every trading minute. Data for daily prices, returns, volumes, number of shares outstanding, ownership concentration and data related to margin-trading and short-selling are obtained from China Stock Market& Accounting Research (CSMAR) and WIND database. Bid and ask prices are drawn from RESSET high-frequency database. All databases provide comprehensive and professional data, including data on the stock market and corporate governance of listed firms in China.

In Chapter 5 and 6, all data are on the daily based (as spreads are calculated using high-frequency data but still on the daily bases). In Chapter 7, I use the intraday data, including the 1-minute bid price, ask price, trading price, return, and trading volume to estimate the changes of liquidities and returns during the day. The sample period in Section 7 is from September 22nd, 2014 to December 11th, 2016(the beginning of the 5th lifting bans on margin-trading and short-selling to the beginning to the 6th lifting bans event; see **Table 2**). Different from the daily data, this intraday, 1-minute frequency data could provide more detail and accurate information about

[15] Many Chinese studies in which researchers exclude stocks from Growth Enterprise Market (GEM)board and Small and Middle-sized Enterprise (SME) board. Stocks from these two boards are considered immature and highly volatile. There are totally 2780 stocks listed in the market and nearly 1000 stocks are listed on the GEM and SME boards.

the price discovery process and the lead-lag relationship in liquidities between margin and non-margin stocks in the specific market situations. The Chinese stock market begins at 9:15, and during the first 15 minutes, there is no actual trading being executed, but only call auction. Then from 9:30 to 11:30 and from 13:00 to 15:00, there are totally four hours (i.e. 240 minutes) trading time. For each stock, the trading price, bid price and ask price are obtained at the end of each minute while 1-minute trading volume is the total value being traded during the one minute. All the high-frequency data are collected from RESSET high-frequency database, a professional financial database in China. The other daily data and firm-specific information like firm size are collected from CSMAR and WIND.

4.2 Liquidity Measure

In this thesis, to measure the liquidity from diverse aspects, spreads and price impact ratios are used as liquidity measures. First, to measure the transaction cost of trading stocks, spreads including relatively quoted spread and relative effective spread are calculated. In most studies (e.g. Benston and Hagerman, 1974; Branch and Stoll, 1978; Stoll, 2000), spreads are used to measure the liquidity since spreads measure the cost of transaction in straightforward way. Fong et al. (2017) compare several liquidity measures and find that the daily closing relative quoted spread is the best percentage-cost proxy for liquidity. Therefore, to obtain the daily relative quoted spreads, daily quoted spreads are first calculated at the market close as we obtain both the bid and ask prices at the market close from 2010 to the end of 2016.[16] Then the relative quoted spread is calculated using the equation below.

[16] Because SSE and SZSE have different closing time, the closing bid and ask prices for stocks listed in SSE are drawn at the time of 15:01 while for stocks listed in SZSE, the closing time is 14:57.

$$\text{Relative Quoted Spread } = \frac{a-b}{m} = \frac{a-b}{(a+b)/2}$$

The other transaction-based liquidity measurement is the relative effective spread. According to Stoll (2000) and Fong et al. (2017), the effective spread is used as the benchmark for transaction-based liquidity measures. The relative effective spread at k^{th} minute is defined as

$$\text{Relative Effective Spread}_k = 2 \cdot |\ln{(P_k)} - \ln{(M_k)}|$$

To obtain the relative effective spread on the daily basis, I first calculate the intraday minute-based relative effective spreads, then calculate the value-weighted average using the trading volume for each minute.

$$\text{Relative Effective Spread} = \frac{\text{Trading volume (in RMB value)}_k}{\text{Total trading volume (in RMB value)}} \cdot 2 \cdot |\ln{(P_k)} - \ln{(M_k)}|$$

For each stock, the daily relative effective spread is the RMB-volume-weighted average of relative effective spread over one day period. More specifically, I first calculate the relative effective spread for every stock every minute, then use the trading volume (in RMB) of every minute as the weights to compute the weighted average relative effective spread for every trading day. All spreads are winsorized by replacing the observations of the upper and lower 0.5% while all non-positive spreads are also eliminated.

According to Fong et al. (2017), the daily relative quoted spread is the measurement that has the highest correlation with the daily relative spread, so the relative spread can be viewed as the best daily percentage-cost proxy for liquidity. In this thesis, I also find that these two transaction-based liquidity measures are highly correlated (see **Table 7**). As a result, in Chapter 5, I will use both spreads measurements as the transaction cost liquidity measures. In Chapter 6 and 7, I only use the benchmark measurement, the relative effective spread, as the transaction cost liquidity proxy.

Apart from the transaction cost, the price impact measurements are also widely used in literature, which captures the resiliency of liquidity. One of the most widely used measure is Amihud's (2002) Illiquidity ratio (e.g. Pastor and Stambaugh, 2003; Goyenko et al., 2009; Hasbrouck, 2009; Adrian et al., 2017). The daily Amihud's Illiquidity ratio is calculated using following equation:

$$\mathrm{ILLQI}_t = \frac{|R_t|}{Vol_t}$$

where R_t is the return for the stock on day t and Vol_t is the volume (in RMB value) on that day. As Fong et al. (2017) argued, the daily Amihud's Illiquid ratio is "the best daily cost-per-dollar-volume proxy". Moreover, I also use Florackis, Gregoriou and Kostakis's (2011) improved version to measure price impact.

$$\mathrm{PriceImpact}_t = \frac{|R_t|}{Turnover_t}$$

where $Turnover_t$ is the turnover (equals to trading volume over total market capitalization) on that day.

Though the Price Impact Ratio of Florackis, Gregoriou and Kostakis's (2011) extends the Illiquid Ratio of Amihud (2002) by eliminating the possible influence of firm size, which is directly related to the trading volume that used in the Amihud's Illiquidity Ratio, the Amihud's Illiquid ratio is still the most widely used liquidity measurement that captures the resiliency aspect of liquidity. In **Table 7**, it is found that these two price impact ratios are high correlated (correlation coefficient is over 0.6). Therefore, only the Amihud's Illiquid Ratio is used as the price impact measure in Chapter 6 and 7.

Therefore, in this thesis, four measurements of liquidity—Relative Quoted Spread, Relative Effective Spread, Amihud's Illiquidity Ratio and Price Impact Ratio, are used in order to grasp different aspects of liquidity in Chapter 5. Then in Chapter 6 and 7, I only use the Relative Effective Spread and Amihud's Illiquidity Ratio as liquidity measures. Though these measurements are called liquidity measures, they all measure the illiquidity of the market. For example, higher spreads indicate higher trading costs and less market tightness.

In **Table 7**, I present the summary statistics and correlation coefficients of these liquidity measures. The relative quoted spread is calculated at the market close for every stock at a daily basis. The relative effective spread is the volume-weighted average of minute relative effective spread on a daily basis. Amihud's Illiquid Ratio is defined as the daily absolute return to the trading volume (in RMB value) while the Price Impact Ratio is calculated using daily absolute return to the turnover. It is found that all four liquidity measures used in this study are negatively correlated with turnover and volume. As all liquidity measurements in this study actually measures illiquidity (the higher the measurement value, the lower the liquidity) while turnover and volume are used to measure liquidity in most literature, this result implies that our liquidity measurements are, at least, consistent with each other and with the traditional measurements. In addition, relative quoted spread and relative effective spread have a correlation coefficient of approximately 0.5, which infer that they are partly related to each other also make sense since both measures are spreads and aimed to measure the tightness of liquidity. Similarly, the relatively higher relationship between Amihud's Illiquid Ratio and Price Impact Ratio also verifies that

Table 7. Summary Statistics and Correlation Coefficients of Liquidity (Illiquidity) Measures

Panel A. Summary Statistics of Liquidity Measures

Variables	Mean	Minimum	Median	Maximum	Standard Deviation	Observations
Relative Quoted Spread	0.1469%	0.0162%	0.112%	0.9429%	0.1277%	3,430,172
Relative Effective Spread	0.1839%	0.0502%	0.1583%	1.0838%	0.1143%	3,724,457
Amihud's Illiquid Ratio	5.46×10^{-10}	0	2.19×10^{-10}	8.33×10^{-9}	9.97×10^{-10}	3,755,876
Price Impact Ratio	1.58272	0	0.845474	21.39539	2.453813	3,755,876

Panel B. Correlation Coefficients of Liquidity Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Relative Quoted Spread (1)	1					
Relative Effective Spread (2)	0.480	1				
Amihud's Illiquid Ratio (3)	0.249	0.284	1			
Price Impact Ratio (4)	0.173	0.190	0.606	1		
Turnover (5)	-0.166	-0.100	-0.173	-0.274	1	
Volume (6)	-0.166	-0.171	-0.228	-0.0996	0.373	1

Panel A shows the summary statistics of four illiquidity measures that will be used in this thesis. Relative Quoted Spread is daily quoted spread calculated at market close; Relative Effective Spread is daily volume-weighted average of one-minute relative effective spread; Amihud's Illiquid Ratio is calculated as the ratio of absolute daily return to the trading volume (in RMB); Price Impact Ratio is the ratio of absolute daily return to the turnover. Panel B shows the correlation coefficients between the four illiquidity measures and two traditional liquidity measures: turnover and volume. All these (il)liquidity measures are calculated on a daily basis.

they have some inner correlation as they both measure the price impact aspect of liquidity. However, spreads and price impact measures are not highly correlated with each other, implying that they can capture different dimensions of liquidity.

To illustrate the overall trends of liquidity, I calculate equally-weighted average of liquidity of all stocks that listed in both Shanghai and ShenZhen Stock Exchange as the market average liquidity from March 2009 to the end of 2016 and plot in **Figure 2**. From the Panel A and B in **Figure 2**, we find a co-movement with relative quoted spread and relative effective spread. Moreover, the two measurements of price impact also move in a similar pattern over time. However, we fail to find out any evident change in the trends of liquidity measures over time. At the first event, only 90 stocks were allowed for margin-trading and short-selling while there were around 2000 stocks in the market. Until the end of 2016, less than half of the stocks in the market were eligible for margin-trading and short-selling. Therefore, it is natural that we failed to find out any trends in the market average liquidities as the impact from eligible stocks may be overwhelmed by the rest stocks in the market.

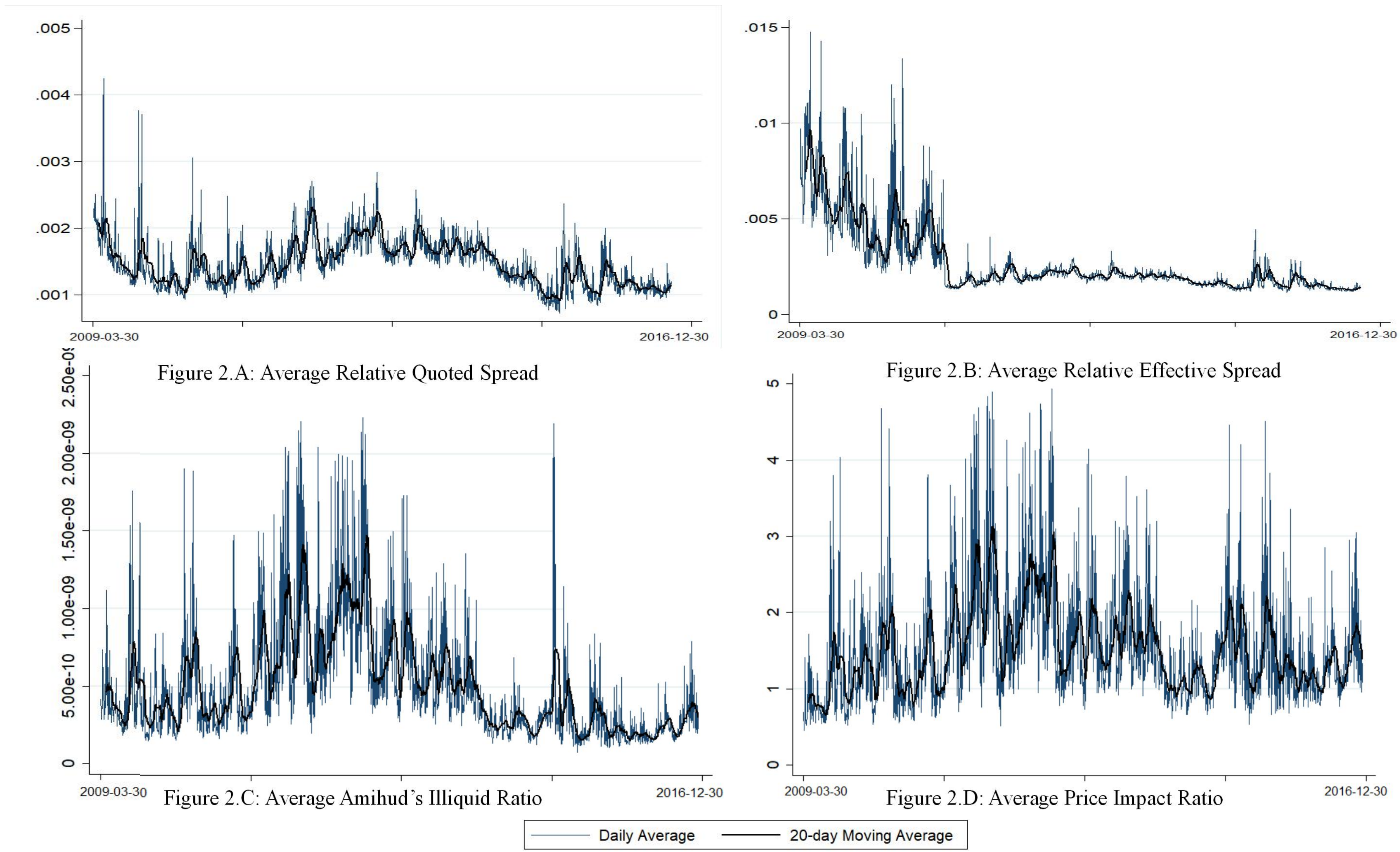


Figure 2. Market Average of Liquidity Measures

This figure shows the daily average and 20-day moving average of four liquidity measures: relative quoted spread, relative effective spread, Amihud's Illiquid Ratio and Price Impact Ratio, from March 2009 to the end of 2016. The thin blue line represents the daily average of liquidity measure while the black line is the 20-day moving average.

4.3 Margin Trading and Short Selling Variables

In order to examine the impact of lifting bans on stocks' liquidities, bans on margin-trading and short-selling were measured using one dummy variable[17], which represents the status of these two activities: eligible (MS = 1) or prohibited (MS = 0).

To further investigate the impact of margin-trading and short-selling on liquidity, two variables are applied. For short selling, one variable used as measurement of the level of short selling trading was short interest ratio. It is defined as the proportion of short interest to the total number of shares outstanding where short interest is the difference between the number of shares shorted and shares already repurchased. As used in many studies, researchers believed that short interest could disseminate information about the market situation to investors (Diamond and Verrecchia, 1987; Senchack and Starks, 1993; Desai et al., 2002; Lamont and Stein, 2004; Asquith, Pathak, and Ritter, 2005; Akbas, Boehmer, and Sorescu, 2017). For example, Diamond and Verrecchia (1987) suggested that an unexpected raise inferred negative news to investors. Senchack and Starks (1993) further proved that stocks with an unexpected increase in short interest generated negative abnormal returns.

$$\begin{aligned} &\text{absoult short interest on day } t \\ &\qquad = \text{short interst on day } t-1 + \text{share shorted on day } t \\ &\qquad - \text{share repurchased on day } t \end{aligned}$$

[17] Here I use only one dummy variable, instead of two, to show the permit/ban on these two activities because the ban or permit on margin-trading and short-selling became effective simultaneously.

$$\text{relative short interest} = \frac{\text{total share shorted} - \text{toatal share repurchased}}{\text{number of shares outstanding}}$$

For margin trading, we use finance interest ratio as measurement of margin trading activity. Similar to short interest ratio, it is defined as the finance interest (in number of shares) to the number of shares outstanding and the finance interest are the number of shares that borrowed yet not repaid.

$$\begin{aligned}&\text{absoult finance interest on day } t \\ &\qquad = \text{finance interest on day } t-1 + \text{margin financed on day } t \\ &\qquad - \text{margin repaid on day } t\end{aligned}$$

$$\text{relative finance interest} = \frac{\text{total margin financed} - \text{total margin repaid}}{\text{number of shares outstanding}}$$

Instead of using short interest or finance interest, I calculate the ratio in order to adjust difference in the number of shares.

Some researchers use short turnover and finance turnover to measure the margin-trading and short-selling activities (e.g. Boehmer and Wu, 2013; Li et al., 2018). Different from relative short interest and relative finance interest, which measures the position of margin-traders and short-sellers, short turnover and finance turnover focus more on the trading activities. Similar to the definition as trading turnover, the short and finance turnover is defined as the ratio of

$$\text{short turnover} = \frac{\text{Volume of shares be shorted}}{\text{Total trading volume}}$$

$$\text{finance turnover} = \frac{\text{Volume of shares be margin borrowed}}{\text{Total trading volume}}$$

In **Table 8**, the summary statistics and correlations of finance interest (also known as finance balance), short interest, finance turnover, and short turnover is presented. Mean of relative short interest and short turnover is only 0.0119% and

0.7939%, indicating that short-selling activities only account for tiny portion in the Chinese

Table 8. Summary Statistics and Correlation Coefficients of Margin-trading and Short-selling Variables

Panel A. Summary Statistics of Margin-trading and Short-selling Variables

Variables	Mean	Minimum	Median	Maximum	Standard Deviation	Observations
Relative Short Interest	0.0119%	0	0.00534%	0.1022%	0.017%	805,427
Relative Finance Interest	5.1356%	0.0233%	4.2578%	19.0166%	4.0584%	805,427
Short Turnover	0.7939%	0	0.1225%	9.1329%	1.4697%	805,427
Finance Turnover	17.3924%	0.0686%	17.5658%	41.0175%	8.5293%	805,427

Panel B. Correlation Coefficients of Margin-trading and Short-selling Variables

	(1)	(2)	(3)	(4)
Relative Short Interest (1)	1			
Relative Finance Interest (2)	-0.0917	1		
Short Turnover (3)	0.485	-0.193	1	
Finance Turnover (4)	-0.0394	0.542	-0.0484	1

Panel A shows the summary statistics of four variables that measure the positions and trading activities of margin-trading and short-selling. Panel B shows the correlation coefficients between the four measures.

market. In contrast, though relative finance interest has mean of 5.14%, the mean of finance turnover is 17.39%, suggesting that near to one fifth of the daily stock transaction is through margin-trading. In panel B of **Table 9**, it is found that margin-trading measures are negatively related to short-selling activities. The correlation between relative short interest and short turnover is 0.48 while the correlation between relative finance interest and finance turnover is 0.54, inferring that margin-trading and short-selling measures are somehow inter-related.

CHAPTER 5: DETERMINANTS OF LIQUIDITY

5.1 Introduction

Liquidity is vital to participants in the stock market. For investors, it would affect stock's return, and in turn, investor's profit (Amihud and Mendelson, 1988). For firms, it could impact capital structure and investment opportunities (Frieder and Martell, 2006; Becker-Blease and Paul, 2006; Banerjee, Gatchev, and Spindt, 2007; Lipson and Mortal, 2009). Its significance thus accounts for a well-established investigation for determinants of liquidity in developed market (e.g. Demsetz, 1968; Benston and Hagerman, 1974; Branch and Freed, 1977; Stoll, 1978; Stoll and Whaley, 1983; Chordia et al., 2000; Stoll, 2000; Chordia et al. 2002). Through both theoretical model and empirical analysis, they find that firm's trading activities (e.g. price, volume, volatility, trading scales), size, ownership structure and its corporate governance are determinants of liquidity. In addition, researchers proposed that trading mechanism and trading venues would also affect liquidity (Branch and Freed ,1977; Hasbrouck and Schwartz, 1986; Brown and Zhang, 1997). With the development of emerging market, more researchers start to focus on investigating these markets and draw comparisons with developed markets. For example, Fong, Holden, & Trzcinka (2017) found that emerging markets tend to have lower market liquidity than stock markets in the developed countries. As the largest emerging market, the Chinese stock market is different from many other markets. The Chinese stock market is a pure order driven market with no market markers to provide liquidity as in the U.S. market. Moreover, individual investors dominate the market rather than institutional investors (Yao, Ma, & He, 2014). Most importantly, there are many trading rules that are unique in the Chinese stock market like the price limit rule. Therefore, in this section, I will examine the determinants of liquidity in the Chinese stock market and whether they will be different from those in developed markets.

Many empirical evidences suggest that firm's trading characteristics like price, volume, volatility and trading scale can influence stocks' liquidities. In early studies, price, volume and trading scale are already found to be negatively related to the bid-ask spread while volatility is positively related (Demsetz, 1968; Tinic, 1972; Benston and Hagerman, 1974; Branch and Freed, 1977; Stoll, 1978). Moreover, the number of shareholders is proposed to influence the spread (Benston and Hagerman, 1974; Branch and Freed ,1977; Stoll, 1978). Studies of Stoll (2000) and Chordia et al. (2000) extend the early studies by including other liquidity measures, larger sample size and longer time period and both find some consistent evidence that trading activity variables such as stock prices, volatility and trading volume, are correlated to liquidity. For example, Stoll (2000) argues that relative quoted spreads were negatively related to volume and price and positively related to the stock's volatility. However, the number of trades affects spreads in NYSE/AMSE while it negatively impact on spreads in NASDAQ. Karolyi et, al. (2012), using cross-sectional test and time-series test, conclude that market volatility and trading activities do impact the liquidities in different countries.

In addition, some researchers argue that firm size will positively affect stock liquidity and firms with larger size would have lower transaction cost. Stoll and Whaley (1983) found that the proportional bid-ask spread for small-sized firms were larger than that for large-sized firms. According to Amihud and Mendelson (1988), investors who hold stocks with higher transaction cost would require higher return for compensation. Stoll (2000) compares the NYSE/AMSE to Nasdaq and found that firm size was positively related to the spreads in NYSE/AMSE while negatively associated to spreads in Nasdaq.

Moreover, the ownership structure is also considered as a determinant of liquidity (e.g. Kamara et, al., 2008). Heflin and Shaw (2000) contend that higher block ownership would cause lower liquidity. Similarly, other researchers also find evidences to support that higher block ownership would hinder firm’s stock liquidity (Brockman et al., 2009). Jacoby and Zheng (2010) extend the work of Heflin and Shaw (2000) and argue that firm size played a significant role in the relationship between market quoted depth and changes in block shareholding of Nasdaq stocks. In contrast, Rubin (2007) find a mixed impact that the level of institutional investors would improve the liquidity while the concentration of institutional investors would negatively influence the liquidity.

As the largest emerging market over last two decades, Chinese stock market has gained growing attention. However, the Chinese stock market is different from many other stock markets in several aspects. First, different from the U.S. market and many European markets which are quote driven, the Chinese stock market is a pure order driven market with no market markers. In the literature, the number of market makers is positively associated to transaction cost (Branch and Freed ,1977; Stoll, 1978; Grossman and Miller, 1988; Stoll, 2000). Chai, Faff and Gharghori (2010) suggest that in a pure order driven market, since public limit orders provide liquidity and establish the bid and ask prices in the absence of market makers, the market characteristics provide more transparent trading environment to market participants. This difference in the trading mechanism would affect the impact of liquidity determinant's explanation power. Brockman and Chung (2002) use data from Hong Kong stock market, which is also an order-driven market and proposed that firm size lost its explanatory power in market bid-ask spread changes. However, Chai et, al. (2010) suggest that trading activity characteristics like price, volume and volatility are still determinants of liquidities using six different monthly low-frequency liquidity measures including spreads, turnover, Amihud's Illiquidity ratio and zero return and zero trading measures in Australia stock market to test whether trading activities were still determinants of liquidities in order-driven market. Malinova and Park (2013) compare the impact of trading mechanism on liquidity and price discovery in order-driven market and quote-driven market and they find that small orders had lower price impacts in the order-driven market than in the quote driven market. In their studies, prices are more efficient and trading volume is higher in a limit order market. Therefore, the difference in trading mechanism does affect the market's liquidity.

The second difference is the investor segmentation. Individual investors are the dominating investors in the Chinese stock market, rather than institutional investors compared to the developed stock markets (Yao, Ma, & He, 2014). In the Chinese stock market, over 99% investors are retail investors, which seems to be abnormal in most developed security markets.

Last, Chinese stock market has its special trading regulations, which is explained in Section 3.5. For example, stock prices can only move by 10% from closing price of previous trading day. This special regulation is called price limit and is designed to protect investors from unlimited losses and stabilize the market. Another distinctive feature in the Chinese stock market is the T+1 rule. Investors cannot sell the stock on the day they buy the stock, they have to wait till tomorrow to execute the transaction. There are also trading restrictions on stocks if they have special treatments (ST). Stocks in the Chinese stock market have their trading status according to the firm's performance. Generally, stocks with special trading status would have more trading restrictions like lower price limit.

In this Chapter, the relevance of determinants of liquidity in longstanding literature in the Chinese stock market is firstly examined. Will those variables perform differently because of the specific nature of the Chinese stock market? In addition, I also investigate the impact of some special trading regulations that are unique in the Chinese stock market. All the determinants tested and proved in this chapter would be used as the control variables in the following two chapters so as to eliminate unobserved heterogeneity.

5.2 Data Description and Methodology

The sample period for this chapter is from 31st March 2010, the first date when margin-trading and short-selling were allowed in the Chinese stock market, to the end of 2016. All stocks listed on Shanghai Stock Exchange (SSE) and ShenZhen Stock Exchange (SZSE) are included in the sample set. The liquidity measures used in this chapter are relative quoted spread, relative effective spread, Amihud's Illiquid Ratio and Price Impact ratio that mentioned in Section 4.2. All liquidity measures are calculated on a daily basis. Bid price, ask prices and stock price used to calculate quoted spread are collected at the market close. Effective spread is the volume weighted average calculated using minute effective spread and cumulated trading volume. Return and trading volume used to calculate the Amihud's Illiquid Ratio are stock's daily return and trading volume in RMB value and turnover in the Price Impact ratio is calculated using daily trading volume over stock's firm size.

In order to examine determinants of liquidity in the Chinese market, several liquidity-determinant variables are extracted from previous literature, including share price, volatility, trade number, volume, firm size, ownership concentration, return etc. The summary statistics of these variables are showed in **Table 9**. Return is calculated as the percentage change in the price on a daily basis. According to the trading rules in the Chinese stock market, the minimum/maximum of daily return is -/+10% while the average of daily return is 0.097%. Volatility is the moving standard deviation of returns based on the previous 20 days' observations. Trade Number is the number of trades executed successfully on that day, which used to represent the trade scale. Firm size is calculated as the total market value of all shares (including shares not available for trading in RMB value) while Market Value is the market value of tradable shares (in RMB). The Ownership Concentration is measured by the percentage of shares

Table 9. Summary Statistics for Possible Liquidity Determinant Variables

Variables	Mean	Minimum	Median	Maximum	Standard Deviation	Observations
Return	0.040%	-10%	0.097%	10%	2.735%	3424857
Price	15.95	2.44	11.95	96.50	13.48	3424857
Volatility	2.808%	0.785%	2.507%	9.084%	1.310%	3424857
Trading Volume	1.45×10^{08}	2268024	6.08×10^{07}	2.24×10^{09}	2.61×10^{08}	3424857
Turnover	2.820%	0.066%	1.676%	25.484%	3.445%	3424857
Trade Number	6823.30	210	3567	82343	10088.52	3424857
Firm Size	1.11×10^{10}	9.24×10^{8}	4.96×10^{09}	2.14×10^{11}	2.28×10^{10}	3424857
Market Value of tradable shares	8.45×10^{09}	3.10×10^{08}	3.44×10^{09}	1.93×10^{11}	1.97×10^{10}	3424857
No. of Shares Outstanding	8.32×10^{08}	1.37×10^{07}	3.10×10^{08}	2.08×10^{10}	2.19×10^{09}	3424857
Ownership Concentration	34.31%	0.907%	32.54%	91.00%	22.58%	3424857

(in RMB). The Ownership Concentration is measured by the percentage of shares owned by 10 largest outstanding shareholders to the total number of shares outstanding. The Institutional Shareholdings are the percentage of shares hold by institutional investors (exclude financial institutions) to the total shares. Turnover refers to the proportion of number of shares traded to the total number of shares outstanding. Volume is the daily value of shares (in RMB) traded while the Price is obtained at the market close.

In **Table 10**, the correlation coefficient matrix for these variables that will be used in the regressions in the next section is first presented. Both used as liquidity measures in early research, turnover and volume are positively correlated. Volatility and trade number are also correlated to these two variables. The trade number are highly correlated to trading volume as the correlation coefficient is 0.928. Another pair that has unusual high correlation is firm size and market value of tradeable shares (correlation=0.945). Both variables can be used as measures of stock's firm size and therefore, firm size is included in the following regressions.

Model used for regression is a linear regression model absorbing two levels of fixed effects: firm level and day level. First, a univariate regression is performed for each liquidity determinant to examine their impact on liquidity. Once these determinants are examined one by one, all of them are put together in the panel regression to investigate their overall impact on liquidity.

Liquidity measures used in the following regressions are relative quoted spread, relative effective spread, Amihud's Illiquid ratio and Price Impact ratio, all of which measure the illiquidity. Their summary statistics and correlation coefficients matrix are showed in **Table 7** (Section 4.2). Determinants used in the regression include price, firm size, volume, turnover, volatility, trade number, ownership concentration ratio and institutional shareholding ratio. Both firm-level fixed effect and time-level fixed effect are included. Standard errors are clustered by both firms and dates.

Table 10. Correlation Coefficient Matrix for Some Liquidity Determinant Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Turnover (1)	1								
Volume (2)	0.355***	1							
Return (3)	0.0886***	0.0742***	1						
Price (4)	0.289***	0.190***	0.0273***	1					
Volatility (5)	0.491***	0.315***	0.00577***	0.254***	1				
Trade Number (6)	0.387***	0.928***	0.0586***	0.0623***	0.338***	1			
Firm Size (7)	-0.0915***	0.495***	0.00607***	0.102***	-0.0473***	0.435***	1		
Market Value of tradable shares (8)	-0.130***	0.485***	0.00641***	0.0479***	-0.0614***	0.423***	0.945***	1	
Ownership Concentration (9)	-0.372***	0.0769***	0.00761***	-0.198***	-0.102***	0.0782***	0.220***	0.330***	1

5.3 Overall Regressions

In this section, whether the determinants of liquidity in the literature (mentioned in Section 5.1) are also determinants in the Chinese stock market is examined first. In addition, I also tested some variables that are unique in the Chinese stock market. In **Table 11**, I present results from univariate panel regression using some widely used determinants of liquidity including price, firm size and other trading activities as the independent variable. All independent variables used in regressions are in logarithm, except institutional shareholding ratio and return. Consistent with previous studies (e.g. Demsetz, 1968; Tinic, 1972; Benston and Hagerman, 1974; Branch and Freed, 1977; Stoll, 1978; Chordia, Roll and Subrahmanyam, 2000; Roll, 2000), price is negatively associated with spreads and two price impact measures. Firm size is also negatively correlated to stocks' spreads and price impacts, consistent with Stoll and Whaley (1983). Volume and turnover, as two simple measures of liquidity in early research, are also negatively related to these illiquidity measures. Different from literature, volatility is negatively correlated to my illiquidity measures. This could just be caused by only including volatility alone as independent variable as volatility is included along with other variables in the regression in previous studies. Trade number is negatively related to stock's spreads and price impact measures, indicating that more trades lead to higher liquidity. Ownership concentration ratio is positively associated with illiquidity measures, suggesting that block-holders may be investors that not actively trade over time so they hinder the market liquidity. This impact of ownership concentration is consistent with the finding of Rubin (2007). In addition, higher returns seem to improve the liquidity, except for the Price Impact ratio, which is statistically insignificant.

Some of determinants can interfere with one another when including them in one regression. For example, from **Table 10**, it is found that trade number and trading volume are highly correlated. Though trade number is a determinant of liquidity, it is inappropriate to include it in the regressions along with trading volume. Similarly, trading volume and turnover are both used as simple liquidity measures and they are also interrelated so there is no need to include them both in the same regression. Therefore, in the regression containing several determinants at once, determinants used are price, firm size, trading volume, volatility, ownership concentration and return. Apart from this, I also include one lagged term of each illiquidity measurements (i.e. AR(1) term) in each regression since liquidity is auto-correlated. The results of regressions are presented in **Table 12**.

Consistent with literature, stock's trading characteristic like price and volume are negatively related to spreads and price impacts. The coefficients of volatility in this regression are positive and statistically significant, which is also consistent with literature. Compared to the results from last regression, this suggests that the impact of volatility on liquidity would be opposite when controlled for other trading characteristics. Firm size seems to decrease spreads and Amihud's Illiquid Ratio, which is also consistent with previous empirical findings while its impact on Price Impact ratio is opposite. Ownership concentration would decrease the stock's liquidity.

Table 11. Coefficients on Liquidity Determinants from Univariate Panel Regression Models

	price	firm size	volume	turnover	volatility	trade number	ownership concentration	return
Relative Quoted	-0.569***	-0.452***	-0.175***	-0.131***	-0.257***	-0.174***	0.0527***	-0.841***
Spread	(0.00834)	(0.00889)	(0.00231)	(0.00235)	(0.00476)	(0.00270)	(0.00368)	(0.0447)
Relative	-0.292***	-0.288***	-0.121***	-0.0945***	-0.129***	-0.142***	0.0485***	-0.511***
Effective Spread	(0.00785)	(0.00693)	(0.00188)	(0.00193)	(0.00411)	(0.00216)	(0.00273)	(0.0452)
Amihud's Illiquid	-0.646***	-0.920***	-0.679***	-0.577***	-0.832***	-0.707***	0.0399***	-0.932**
Ratio	(0.0170)	(0.0181)	(0.00374)	(0.00526)	(0.0122)	(0.00431)	(0.00634)	(0.454)
Price Impact	-0.303***	-0.144***	-0.472***	-0.666***	-0.625***	-0.508***	0.382***	-0.527
Ratio	(0.0150)	(0.0151)	(0.00487)	(0.00391)	(0.0115)	(0.00521)	(0.00550)	(0.454)

There are four illiquidity measures used as dependent variables: Relative Quoted Spread, Relative Effective Spread, Amihud's Illiquid Ratio and Price Impact Ratio. These variables are taken logarithm form so that their distributions are more likely to be normal. Price, Firm size, Volume, Turnover, Voaltility, trade number, and Ownership Concentration are also in logarithm. All regressions are controlled for the time effect as for every day, one daily dummy variable is included in the regression and for each firm, the fixed effect is used. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

Table 12. Determinants of Liquidity from Panel Regressions

VARIABLES	Relative Quoted Spread	Relative Effective Spread	Amihud's Illiquid Ratio	Price Impact Ratio
Price	-0.382***	-0.108***	-0.0160**	-0.107***
	(0.00891)	(0.00567)	(0.00635)	(0.00813)
Firm Size	-0.0931***	-0.0600***	-0.218***	0.557***
	(0.00629)	(0.00445)	(0.00772)	(0.0107)
Volume	-0.0890***	-0.0700***	-0.634***	-0.543***
	(0.00204)	(0.00142)	(0.00401)	(0.00411)
Volatility	0.0103***	0.0502***	0.115***	0.0627***
	(0.00304)	(0.00234)	(0.00607)	(0.00647)
Ownership Concentration	0.0150***	0.0200***	0.00476**	0.355***
	(0.00180)	(0.00136)	(0.00206)	(0.00363)
Return	0.506***	0.903***	-0.569***	-0.896***
	(0.0290)	(0.0270)	(0.118)	(0.117)
AR(1)	0.104***	0.344***	0.0331***	0.0585***
	(0.00184)	(0.00330)	(0.00190)	(0.00214)
Constant	-2.093***	-1.644***	-6.311***	0.248*
	(0.0920)	(0.0648)	(0.116)	(0.149)
Observations	3,035,864	3,035,864	3,035,864	3,035,864
R-squared	0.448	0.585	0.656	0.496

There are four illiquidity measures used as dependent variables: Relative Quoted Spread, Relative Effective Spread, Amihud's Illiquid Ratio and Price Impact Ratio. These variables are taken logarithm form so that their distributions are more likely to be normal. Price, Firm size, Volume, Turnover, Voaltility, and Ownership Concentration are also in logarithm. Because the liquidity is considered to correlated with itself, the AR(1) is the one lag of the dependent variable with a lag time of one day. More specifically, AR(1) represents the lagged relative quoted spread, lagged relative effective spread, lagged Amihud's Illiquid Ratio and lagged Price Impact Ratio. All regressions are controlled for the time effect as for every day, one daily dummy variable is included in the regression and for each firm, the fixed effect is used. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level

The impacts of return are different for spreads and price impact measures. Stocks with high return seems to have higher transaction cost but lower price impact. It is also found that the lagged liquidity term is positively correlated to the liquidity measure, also supporting that liquidity is auto-correlated.

To further investigate the determinant of liquidity in the Chinese stock market, I add three more variable that represent the special trading regulations in China into the panel regression. First, according to the "T+1" rule, investors in the stock market cannot trade the stocks on the same day of transaction. However, investors could trade immediately in the option markets since there is no such regulation in financial derivative markets in China. Therefore, if a stock is the component of the index option, it would be more liquid than other stocks that are not included in the list of index option. Moreover, the index options seem to influence the stock prices in several cases. For example, the prices of three main stock index options[18] drop significantly before the market crash in June 2015. It is natural to speculate whether stocks listed in the index options would influence their trading activities and liquidities. Therefore, to examine whether the list of index option would influence the liquidity, I include one dummy variables to identify the status whether stocks are listed in most commonly traded index option. The index option is HuShen300 (HS300). According to SSE and SZSE, stocks included in HS300 should be large in firm size and high in liquidity. All stocks are ranked by the weighted average of daily market capitalization, market values outstanding, number of shares outstanding and trading volume (both in number of shares and in RMB), then the first 300 stocks are included into HS300 index. The dummy variable is called HS300 and equals to one if the stock is included in the HS300 index.

Another special trading regulation is “Price Limit”. According to the trading regulation of the Chinese stock market, a stock’s price can only move by 10%, either up or down, compared to its closing price from last trading day. The regulator believes that this limit in price movement could partly protect investors and stabilize the market from volatile price movements. However, this regulation would probably decrease the liquidity as investors are reluctant to trade when a stock hits the price limit. For example, when a listed company discloses negative information and most investors are willing to sell its stock. If there is no price limit, the stock price would decrease until it reaches to the expected value of the market. However, when there is

[18] They are: HuShen300 (HS300), ZhongZheng500(ZZ500) and ShangZheng50(SZ50).

a price limit, the stock price can only decrease by 10% and is still higher than its expected value, then very few or even no investors would like to trade this stock, thus the liquidity would be hindered. In fact, once a stock hits the price limit, its liquidity would dry up and trading volume would plummet to a very low level in most cases. To capture this specific trading regulation, I create one dummy variable “Price Limit”, which equals to one if the stock hit the price limit on that trading day.

The third special feature is the trading status. The stock exchange would determine whether a stock is subject to “Special Treatment” according to the underlying firm’s accounting performance. Sometimes, when a company faces some problems (e.g. high probability of bankrupt, high leverage, continuous deficits) that would lead the stock exchanges to believe there is high probability of bankruptcy, its stock would have a trading status as special trading (ST) status. These special trading (ST) stocks would have many restrictions in trading like only 5% price limits. Therefore, ST stocks are believed to be of highly risk. This trading status is actually a warning sign given to the investors. I use another dummy variable “trading status” to measure whether the stock is under special treatment. The dummy variable equals to one is the stock is an ST stock and equals to 0 if the stock is normally traded.

The results after adding three dummy variables that represent the unique trading regulations in the Chinese stock market are showed in **Table 13**. First, the impact of each determinant remains largely the same after considering trading rules in China. Second, dummy variable HS300 is negatively associated to two spreads measures and Amihud’s Illiquid Ratio, which suggests that stocks being components of stock index seems to improve the stock’s liquidity. In addition, price limit is positively related to our liquidity measures, which supports the hypothesis that price limit actually hinders the stock’s liquidity. Finally, it is found that the spreads for ST

Table 13. Determinants of Liquidity including Trading Regulations Variables Unique in China

VARIABLES	Relative Quoted Spread	Relative Effective Spread	Amihud's Illiquid Ratio	Price Impact Ratio
Price	-0.382***	-0.108***	-0.0162**	-0.104***
	(0.00887)	(0.00565)	(0.00629)	(0.00803)
Firm Size	-0.0848***	-0.0553***	-0.215***	0.554***
	(0.00621)	(0.00436)	(0.00756)	(0.0105)
Volume	-0.0887***	-0.0702***	-0.635***	-0.544***
	(0.00203)	(0.00142)	(0.00402)	(0.00412)
Volatility	0.00991***	0.0505***	0.114***	0.0651***
	(0.00300)	(0.00231)	(0.00607)	(0.00645)
Ownership Concentration	0.0153***	0.0199***	0.00477**	0.354***
	(0.00178)	(0.00135)	(0.00204)	(0.00363)
Return	0.503***	0.903***	-0.562***	-0.889***
	(0.0288)	(0.0266)	(0.117)	(0.116)
HS300	-0.0389***	-0.0162***	-0.0177*	0.0518***
	(0.00684)	(0.00583)	(0.0101)	(0.0123)
Price Limit	0.263***	0.412***	0.720***	0.729***
	(0.0725)	(0.0545)	(0.0267)	(0.0268)
Trading Status	0.0756***	0.0618***	-0.0119	0.0829***
	(0.00769)	(0.00614)	(0.00998)	(0.0132)
AR(1)	0.104***	0.341***	0.0331***	0.0582***
	(0.00183)	(0.00333)	(0.00190)	(0.00214)
Constant	-2.236***	-1.730***	-6.339***	0.307**
	(0.0905)	(0.0634)	(0.116)	(0.147)
Observations	3,035,570	3,035,570	3,035,570	3,035,570
R-squared	0.449	0.587	0.657	0.497

There are four illiquidity measures used as dependent variables: Relative Quoted Spread, Relative Effective Spread, Amihud's Illiquid Ratio and Price Impact Ratio. These variables are taken logarithm form so that their distributions are more likely to be normal. Price, Firm size, Volume, Turnover, Voaltility, and Ownership Concentration are also in logarithm. HS300 is a dummy variable which equals to one if a stock is listed in the HS300 index. Price Limit is a dummy variable which equals to one if a stock's closing price increases/decreases by +10%/-10% compared to the closing price from previous trading day. Trading Status is a dummy variable that is equal to one if a stock is special treated. Because the liquidity is considered to correlated with itself, the AR(1) is the one lag of the dependent variable with a lag time of one day. More specifically, AR(1) represents the lagged relative quoted spread, lagged relative effective spread, lagged Amihud's Illiquid Ratio and lagged Price Impact Ratio. All regressions are controlled for the time effect as for every day, one daily dummy variable is included in the regression and for each firm, the fixed effect is used. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level

stocks are higher. According to the risk-return model, ST stocks are stocks with higher risk so a higher return is expected for compensation. Higher stock return is associated with higher transaction cost (Amihud and Mendelson; 1988). Trading status's impact on Amihud's Illiquid ratio is negative but insignificant. In contrast, trading status is positively related to Price Impact Ratio, also suggesting that stocks be special treated would hinder the liquidity.

5.4 Conclusion

In conclusion, as consistent with literature, trading activities like price, volume and volatility, are proved also to be determinants in the Chinese stock market. Moreover, price and volume will reduce both spreads measures and price impact measures, thus improve liquidity while volatility is negatively correlated to liquidity. I also find that larger firm size contributes to higher liquidity using both spread measures and Amihud’s Illiquid measures. In contrast, higher concentration of ownership will lead to higher spreads and price impact. The impact of return on different illiquidity measure is quite the opposite. For relative quoted spread and relative effective spread, higher return is associated with higher spreads. However, in terms of price impact measures, return will reduce the price impact, implying higher liquidity. The impact of these determinants remain the same even after I include three variables that are unique in the Chinese stock market. I find that if stocks are listed in the index HS300, their liquidities tend to increase. In addition, when a stock hits the price limit or is specially treated, the spread will increase and price impact tend to be higher, therefore suggesting a lower liquidity.

CHAPTER 6: THE IMPACTS OF MARGIN-TRADING AND SHORT-SELLING ON LIQUIDITY

6.1 Introduction

As margin-trading and short-selling emerged, several research studies delved into the impact of these activities on the stock market (e.g. Bris, Goetzmann and Zhu, 2007; Hirose, Kato and Bremercan, 2009; Beber and Pagano, 2013; Boehmer et al., 2013; Boehmer and Wu, 2013; Alves, Mendes and da Silva, 2016; Chen et al., 2016; Kahraman and Tookes, 2017). However, most of these studies focus on the U.S. market and only a few investigate the Chinese stock market. For example, after lifting the bans on margin trading and short selling, Chang, Luo, and Ren (2014) find that price efficiency improved and volatility decreased. When comparing margin-trading and short-selling, they argue that the effects of short-selling were more remarkable than that of margin-trading. Sharif, Anderson, and Marshall (2014) also focused on the first introduction of margin-trading and short-selling in March 2010 in the Chinese stock market. They suggest that stocks eligible for margin-trading and short-selling to have lower levels of liquidity than their cross-listed and matched pairs. Chen et al. (2016) expand the existing sample by including more stocks and increasing the time frame. They argue that margin-trading and short-selling could help incorporate existing information into the stock pricing, which would improve price efficiency. Furthermore, Ma et al. (2018) focus on the Chinese stock market and propose that aggregated margin-trading on a market level improves trading activity and liquidity, while short-selling decreases liquidity. Consistent with Chang et al. (2014), Li et al. (2018) find that short-selling improves price efficiency and liquidity while reducing stock volatility.

After the financial crisis during 2008-09, investigations extensively focused on the impacts of short-sellers on stock market return, liquidity, and price discovery. The regulators argue that short-sellers could harm the market. Consequently, they imposed bans on short-sale during this period of the financial crisis.[19] On the other hand, many researchers suggest that bans on short-sale negatively impact market liquidity. For example, the study of Diamond and Verrecchia (1987) includes a theoretical model, which predicts that with constraints on short-sale, the price will adjust more slowly to negative information. As a result, this will impair the stock's liquidity. Boehmer et al. (2012) empirically examine the effect of short-sale bans on the U.S. stock market during the 2008 financial crisis. Short-sale constraints hindered the liquidity of most large-cap stocks and worsened market performance. Beber and Pagano (2013) utilize international data from the 2007 to 2009 financial crisis. While their results suggest that short-sale bans hindered both liquidity and price discovery, some of these suffer from endogeneity given that many of them focus on the crisis period. Instead of the bans on short-selling causing a decrease in liquidity, the financial crisis may have already dried up the market liquidity beforehand. Furthermore, the Chinese stock market is a perfect example to investigate the impact of margin-trading and short-selling. By taking advantage of China's gradual legislation of margin-trading and short-selling where only a few stocks could be eligible, I could avoid this endogeneity problem.

In this chapter, I match the stocks eligible for margin-trading and short-selling to the corresponding non-eligible stocks. Initially, I prove that stocks eligible for margin-trading and short-selling would have higher liquidity. An event study that compares the liquidities of eligible and ineligible stocks before and after the

[19] For example, see Berber and Pagano (2013). They summarized the impact of short-sale bans during the 2007-09 financial crisis period all around the world.

inception dates further proves that lifting bans on margin-trading and short-selling would improve the eligible stocks' liquidities. As I focused on margin-trading and short-selling, I find that margin-trading would increase the stock's liquidity while short-selling hinders liquidity. Moreover, I reason that an increase in adverse selection causes the negative impact of short-selling on liquidity. To support this conjecture, I further prove that short-sellers are informed traders, where an increase in a short-sale position could predict future returns. Moreover, I demonstrate that firms with a high level of information asymmetry mainly cause the negative impact of short-selling on liquidity. However, when focusing on a market crisis period, I find that eligible stocks tend to have lower liquidity. In contrast to a normal market period, the impact of margin-trading and short-selling on liquidity become the opposite. Moreover, short-selling seems to improve liquidity during a crisis.

6.2 Data Description and Methodology

The sample period for this chapter occurs from March 31, 2010, which is the first day after lifting the bans on margin-trading and short-selling to December 11, 2016, which is a day before the 6th inception date (See **Table 2** from Section 3.2). The sample includes all the stocks eligible for margin-trading and short-selling. More specifically, the sample ranges from March 31, 2010 to December 5, 2011, which includes 90 stocks eligible for margin and short selling. Then, from September 22, 2014, the sample contains 900 stocks eligible for both activities.

I also include stocks ineligible for margin-trading and short-selling in the sample. As mentioned in the introduction, I use the matching approach to select stocks that are ineligible for margin trading and short selling to match the eligible stocks. Since the primary purpose of the thesis is to investigate the impact of margin-trading and short-selling on liquidity, I match each margin stock to one non-margin stock according to the industry, as well as the daily closing price, market capitalization, and trading volumes. The selection of matching pairs is executed to reflect the characteristics of the margin stocks as close as possible.

Similar to the matching method used by Huang and Stoll (1996), Bacidore and Sofianos (2002) and Sharif, Anderson, and Marshall (2014), I calculate the sum of squared relative differences and find the pair that minimizes it.

$$\begin{aligned} &Total\ Relative\ Difference \\ &= \left(\frac{price_M - price_N}{(price_M + price_N)/2}\right)^2 + \left(\frac{market\ value_M - market\ value_N}{(market\ value_M + market\ value_N)/2}\right)^2 \\ &+ \left(\frac{volume_M - volume_N}{(volume_M + volume_N)/2}\right)^2 \qquad (1) \end{aligned}$$

For a margin stock, I first calculate the sum of relative price difference square, relative market value difference square, and relative volume difference square between this stock and each non-margin stock within the same industry. Then, I select the stock that has the minimum sum of relative difference squares as the matched non-margin stock given that the ultimate goal for matching is to choose the corresponding non-margin stock that has the price, firm size, and trading volume closest to the margin stock. To minimize the difference in the matching pairs, I exclude matching pairs with the highest one percent of relative differences in price, market value, and trading volume. **Table 14** shows all summary statistics for matching. Panel A shows the characteristics of eligible stocks. Panel B shows the characteristics of matched ineligible stocks. In Panel C, I compare these criteria and calculate the differences in mean and median. Panels A and B highlight that market capitalization and trading volume of eligible stocks are higher than matched ineligible stocks. In Panel C, I execute the t-test to compare the mean values of three matching criteria for eligible and ineligible stocks. It turns out that price, market value, and trading volume of eligible stocks are all higher than matched ineligible stocks. Additionally, I utilize the Wilcoxon matched-pairs test to compare the median of two groups of stocks. The results suggest that eligible stocks have higher median values in both market value and trading volume.

Even after choosing matched pairs with minimum differences in price, market capitalization, and volume, the nature of eligible stocks led to this result. According to the CSRC requirement, the stocks that are on the list allow margin-trading and short-selling are required to be large in firm size and high in trading volume (see Section 3.2). Therefore, to eliminate this effect in future regressions, I include control variables like price, firm size, and trading volume.

After selecting the matching pairs that contain both eligible and ineligible stocks for the sample, I run panel regressions to examine whether the eligibility for margin-trading and short-selling will influence the stocks' liquidities with and without control variables that could also affect liquidity. Thus, the regression equation is:

$$Illiquidity_{it} = \alpha + \beta \times MS_{it} + \boldsymbol{\gamma} \times \boldsymbol{X_{it}} + \varepsilon_{it} \qquad (2)$$

where $\text{Illiquidity}_{\text{it}}$ is the illiquidity measure for stock i on day t; α is the constant of the regression; MS_{it} is a dummy variable that represents whether stock i is eligible for margin-trading and short-selling or not and it is equal to one if stock i is eligible on day t; β is the coefficient on the dummy variable; $\boldsymbol{\gamma}$ is a constant vector; $\boldsymbol{X_{jt}}$ is a vector containing the control variables that include price, volatility, firm size, and other variables that I proved to be determinants of liquidity in the previous chapter; and ε_{ijt} is the error term. In this panel regression, I also control for both day fixed effect and firm fixed effect.

Table 14. Summary Statistics for Matched Pairs

	Mean	Median	Standard deviation	Minimum	Lower quantile	Upper quantile	Maximum
Panel A. Eligible stocks characteristic							
Price	15.93	12.09	13.44	1.51	7.50	19.83	275.86
Market Cap	2.63×10^{10}	1.23×10^{10}	6.72×10^{10}	6.59×10^{8}	7.04×10^{9}	2.39×10^{10}	2.21×10^{12}
Volume	3.71×10^{8}	1.79×10^{8}	6.97×10^{8}	2.46×10^{5}	8.35×10^{7}	3.96×10^{8}	3.91×10^{10}
Panel B. Matched ineligible stocks characteristic							
Price	15.89	12.07	13.31	1.53	7.51	19.80	273.46
Market Cap	8.85×10^{9}	6.93×10^{9}	7.92×10^{9}	2.94×10^{8}	4.58×10^{9}	1.05×10^{10}	3.45×10^{11}
Volume	2.52×10^{8}	1.43×10^{8}	4.01×10^{8}	2.09×10^{5}	6.93×10^{7}	2.95×10^{8}	2.41×10^{10}

Panel C. Difference between eligible and ineligible stocks

	Difference in Mean	T-statistic	Difference in Median	Z-score
Price	0.039***	26.42	0.02	1.17
Market Cap	1.74×10^{10}***	235.21	5.36×10^{9}***	631.92
Volume	1.20×10^{8}***	186.48	3.60×10^{7}***	315.41

In panel A and B, the summary statistics for three matching criteria for eligible stocks and corresponding matched ineligible stocks is showed. Price is the closing price in RMB; Market Cap is the stock's market capitalization (in RMB value), which equals to the total value of shares outstanding; Volume is the stock's trading volume, also in RMB value. All these characteristics are on daily basis. In panel C, the difference in mean and difference in median of three characteristics between eligible and matched ineligible are showed. T-statistic is for the null hypothesis that the difference in means equals to zero. Z-score is from a non-parametric Wilcoxon matched-pairs test of the null hypothesis that the difference in medians equals zero. Three (***) asterisks represent statistically significant at 1% level.

Table 15. Summary Statistics for Illiquidity Measures and Some Control Variables

Variables	Mean	Minimum	Median	Maximum	Standard Deviation	Observations
Relative Effective Spread	0.166%	0.0502%	0.144%	1.08%	0.0961%	1598066
Amihud's Illiquid Ratio	1.84×10^{-10}	0	9.67×10^{-11}	8.33×10^{-09}	2.81×10^{-10}	1598066
Price	15.91	2.44	12	96.50	13.17	1598066
Firm Size	2.16×10^{10}	9.24×10^{8}	1.09×10^{10}	2.14×10^{11}	3.34×10^{10}	1598066
Volume	2.95×10^{08}	2.27×10^{6}	1.58×10^{08}	2.24×10^{09}	3.87×10^{08}	1598066
Volatility	3.03%	0.785%	2.66%	9.08%	1.54%	1598066
Ownership Concentration	43.52%	0.91%	43.63%	91.00%	21.19%	1598066
Return	0.197%	-10%	0.144%	10.02%	3.42%	1598066

Table 16. Correlation Coefficients Matrix for some Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Price (1)	1					
Firm Size (2)	0.214***	1				
Volume (3)	0.377***	0.506***	1			
Volatility (4)	0.282***	-0.103***	0.440***	1		
Ownership Concentration (5)	-0.0867***	0.0017*	-0.117***	-0.0864***	1	
Return (6)	0.0420***	-0.0063***	0.0979***	0.0098***	0.0028***	1

The summary statistics of most variables used in the regression are listed in **Table 15**. The correlation coefficient matrix for the control variables is shown in **Table 16**. It is demonstrated that firm size and trading volume have higher inter-correlation than other variables on an acceptable level.

6.3 Panel Regressions: Overall Impact on Liquidity

Table 17 presents estimates of regressions using equation (1) where the dependent variable is the relative effective spread and Amihud's Illiquid Ratio. All regressions presented in **Table 17** control for the time fixed effect and firm fixed effect. The independent variable is MS, which is a dummy variable described in

Table 17. Panel Regression: Relative Effective Spread, Amihud's Illiquid Ratio, and Status of Eligibility

VARIABLES	(1) Relative Effective Spread	(2) Relative Effective Spread	(3) Amihud's Illiquid Ratio	(4) Amihud's Illiquid Ratio
MS	-0.0211***	-0.0172***	-0.0476***	-0.0469***
	(0.00496)	(0.00338)	(0.0149)	(0.00713)
Price		-0.140***		-0.0132
		(0.00713)		(0.00929)
Firm Size		-0.0596***		-0.204***
		(0.00558)		(0.0134)
Volume		-0.0360***		-0.426***
		(0.00154)		(0.00654)
Volatility		0.0337***		0.0469***
		(0.00249)		(0.00839)
Ownership Concentration		0.00697***		0.00218
		(0.00231)		(0.00453)
Return		0.567***		0.581***
		(0.0210)		(0.103)
HS300		-0.00459		-0.0182*
		(0.00453)		(0.0105)
Price Limit		0.0546***		0.750***
		(0.0132)		(0.0259)
AR(1)	0.549***	0.476***	0.364***	0.250***
	(0.00621)	(0.00606)	(0.00582)	(0.00671)
Constant	-2.937***	-1.314***	-14.69***	-5.771***
	(0.0404)	(0.0829)	(0.134)	(0.196)
Observations	1,389,672	1,385,095	1,389,672	1,385,095
R-squared	0.702	0.718	0.542	0.587

There are two dependent variables: the Relative Effective Spread is the volume-weighted average of minute relative effective spread, Amihud's Illiquid Ratio is on daily basis. These variables are taken logarithm form so that their distributions are more likely to be normally distributed. MS is a dummy variable that equals to one if margin-trading and short-selling are allowed for one stock at any date and zero otherwise. Price, Firm size, Volume, Turnover, Volatility and Ownership Concentration are also in logarithm. Because the liquidity is considered to correlate with itself, the AR(1) is the one lag of the dependent variable with a lag time of one day. More specifically, AR(1) represents the lagged relative effective spread, lagged Amihud's Illiquid Ratio. All regressions are controlled for the time fixed effect as for every day, one daily dummy variable is included in the regression and for each firm, the fixed effect is also used. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

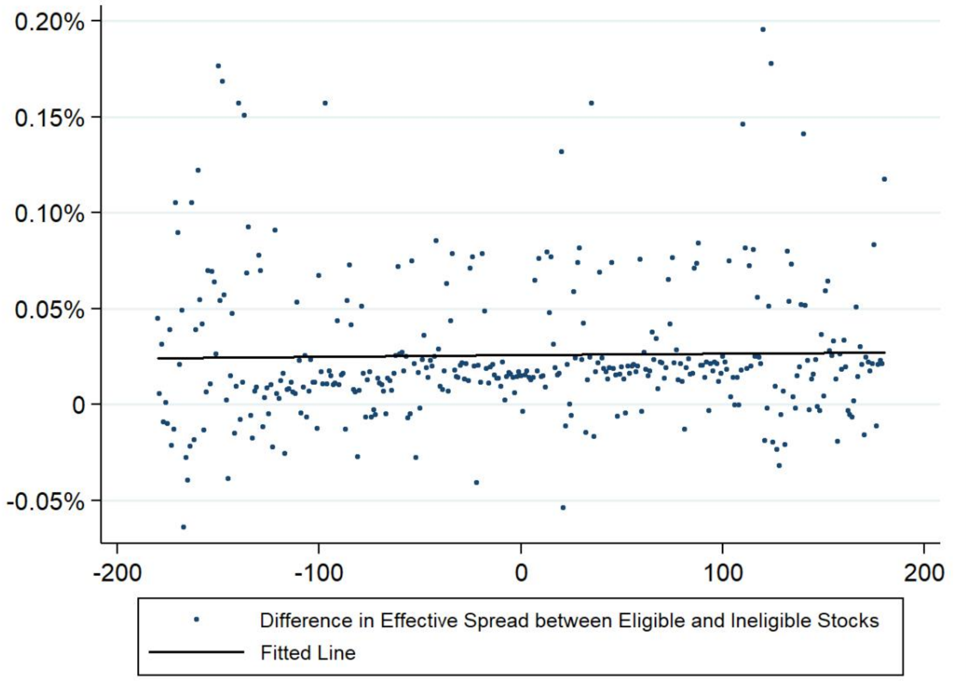
Section 4 and indicates the stock's eligibility for margin-trading and short-selling. Columns (1) and (3) do not have any control variables while columns (2) and (4) include control variables. All the control variables included are determinants from Chapter 5.

The estimates of the MS variable indicate that the eligibility for margin trading and short selling is negatively correlated with both the effective spread and Amihud's Illiquid Ratio regardless of the inclusion of control variables. Columns (2) and (4) demonstrate that trading activity liquidity-determinants like price and volume remain negatively associated with illiquid measures while volatility is positively correlated. Firm size is also negatively correlated to the spreads and Illiquid ratio, just like the results from the literature and Chapter 5 of this thesis.

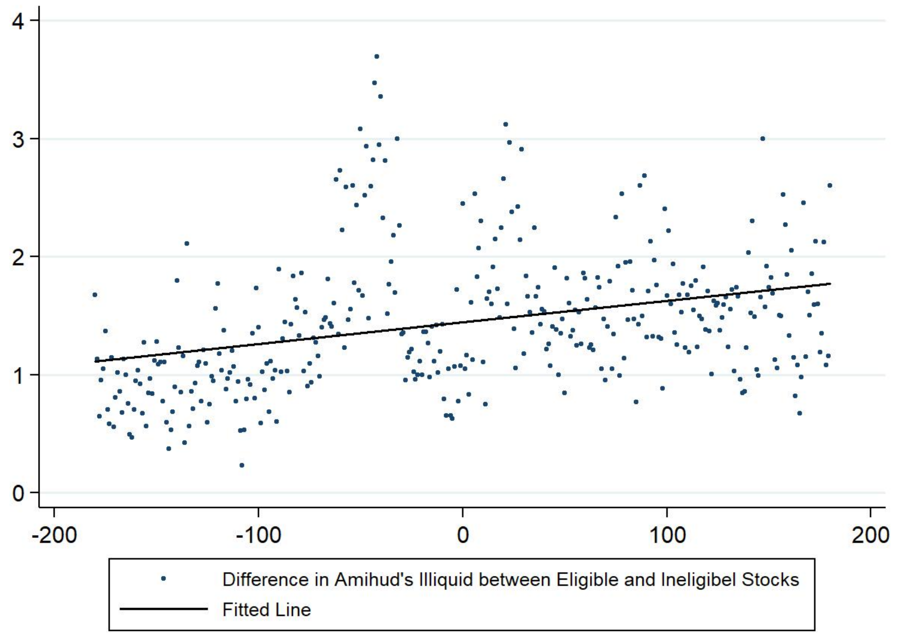
6.4 Event Study Analysis

According to the last panel regression results, stocks eligible for margin-trading and short-selling seem to have higher liquidity than other ineligible stocks. However, this could result from the nature of eligible stocks that tend to have a large firm size and higher price. Though I controlled for firm size, price, volume, and other variables that may contribute to liquidity, this endogeneity problem may still exist. To address this, I apply the event study approach with a 180-day window before and after the inception of lifting the ban. Timing is set as follows: time $t = 0$ is the date in which the ban was lifted (i.e. inception date), time $t = 1$ is the first day after the ban was lifted, time $t = -1$ is one day that precedes the event and so forth. So, time t ranges from -180 to 180. As listed in **Table 2** in Section 3.2, I choose the first five events and compare the liquidities of the newly added stocks 180 days before and

Figure 3. Average Effective Spread and Average Amihud's Illiquid Ratio before and after Inception Date



Panel A: Difference in Average Effective Spread between Eligible and Ineligible Stocks
(Difference = Ineligible stocks – Eligible stocks)



Panel B: Difference in Average Amihud's Illiquid Ratio between Eligible and Ineligible Stocks
(Difference = Ineligible stocks – Eligible stocks)

Panel A plots the difference in average relative effective spread between ineligible and eligible stocks 180 days before and after each inception date in blue dots, and the fitted line for the scatterplot. Panel B plots the difference in average Amihud's Illiquid ratio between ineligible and eligible stocks 180 days before and after each inception date in blue dots, and the fitted line for the scatterplot.

after the inception date.

In the first step, I compare the difference in liquidities between stocks eligible for margin-trading and short-selling and ineligible stocks before and after each event. I first compute the effective spread and Amihud's Illiquid ratio for both eligible and ineligible stocks before and after each event. Then, I calculate the average liquidity for five events. The results highlight that eligible stocks have lower effective spread and price impact compared to ineligible stocks even before bans were lifted. This partially supports the assumption that eligible stocks have features that tend to have higher liquidity than ineligible stocks. The next step is to calculate the liquidity difference

between ineligible and eligible stocks and compare the difference before and after the inception date. In Figure 1, I demonstrate the differences in the effective spread and Amihud's Illiquid ratio using a scatterplot. I also draw fitted lines to highlight the trends of these differences. In both panels, the direction of the fitted lines is upward with a slope of 1.45×10^{-7} in panel A and a slope of 1.84×10^{-3} in panel B. This indicates that the difference between the liquidities of eligible and non-eligible stocks became more extensive after the bans on margin-trading and short-selling were lifted.

After presenting the descriptive evidence, I also pursue another approach to compare the effect of lifting bans on liquidity before and after each event. I run the regression following the same regression specifications (**Equation 2**) from the previous panel regression analysis for days around each event. The event date is chosen as the inception date when particular stocks were allowed for margin-trading and short-selling. For example, 31st March 2010 is the first event date where 90 stocks that were allowed for margin-trading and short-selling have a dummy variable MS_{it} that is equal to 1 throughout the sample period (180 days before and after the event). Therefore, this study contains five events where each event has its sample period[20]. This approach, which is different from previous panel regression, involves a cross-sectional regression that is repeated daily. For each event, the sample contains the newly added stocks in the eligible list and their matched non-eligible stocks. The matching method is the same in the previous section but on a semiannual basis. Instead of using daily price, trading volume, and market value to match a stock in the same industry for each day, I use the average price, trading volume, and market value of stocks pre-event for 180 days as matching criteria to select the ineligible stocks. Once selected, we use them as the matching sample for days both before and post-event dates. The purpose is to ensure that we are using the same ineligible stocks as the comparison group for days both before and after the event dates. The coefficient β_{it} on the dummy variable is recorded for each event occurring on each day (showed in **Table 18** columns (1) to (5)). Also, I calculate the arithmetic mean that is defined as $(\beta_1+ \beta_2+ \beta_3+ \beta_4+ \beta_5)/5$ for each day t (see column (6)). To compare the estimates before and after the event, I apply the t-test. The results are shown in **Table 18**.

In Panel A, the illiquidity measure is the relative effective spread and in Panel B, the illiquidity measure is Amihud’s Illiquid Ratio. In column (1), I present the coefficients on dummy variable MSit 180 days before and after the first event. For both liquidity measures, the effects of allowing for margin-trading and short-selling

[20] For the first event, the sample span is from 2009/07/06 to 2010/12/27; for the second event, the sample span is from 2011/03/14 to 2012/08/30; for the third event, the sample span is from 2012/05/11 to 2013/11/07; for the fourth event, the sample span is from 2012/12/14 to 2014/06/18; and for the fifth event, the sample span is from 2013/12/27 to 2015/06/19.

Table 18. Event Study: Coefficients on Eligibility (MS) Before and After Each Event

	(1)	(2)	(3)	(4)	(5)	(6)
	1st Expansion 31st Mar 2010	2nd Expansion 5th Dec 2011	3rd Expansion 31st Jan 2013	4th Expansion 16th Sep 2013	5th Expansion 22nd Sep 2014	All Expansions
No. of newly added stocks	90	191	276	206	218	981
Panel A. Relative Effective Spread						
Days	-0.0372***	-0.0201***	0.0141***	0.0170***	0.00730***	-0.00396***
(-180,-1)	(0.00520)	(0.00195)	(0.00170)	(0.00205)	(0.00243)	(0.00131)
Days	-0.0361***	-0.00397*	-0.00243*	-0.00787***	-0.00511**	-0.0111***
(+1, +180)	(0.00430)	(0.00208)	(0.00146)	(0.00176)	(0.00210)	(0.00114)
Difference	-0.00108	-0.0161***	0.01652***	0.02490***	0.01241***	0.00719***
(Before-After)	(0.00675)	(0.00285)	(0.00224)	(0.002703)	(0.00321)	(0.00174)
Panel B. Amihud's Illiquid Ratio						
Days	-0.0617***	-0.0192***	-0.0385***	0.00440	0.0530***	-0.0124***
(-180,-1)	(0.0124)	(0.00636)	(0.00503)	(0.00684)	(0.00683)	(0.00359)
Days	-0.0608***	-0.00823	-0.0470***	-0.0406***	0.00706	-0.0298***
(+1, +180)	(0.0115)	(0.00642)	(0.00541)	(0.00591)	(0.00650)	(0.00343)
Difference	-0.00091	-0.01096	0.00852	0.04498***	0.04591***	0.01742***
(Before-After)	(0.01689)	(0.00904)	(0.00739)	(0.00904)	(0.00942)	(0.00497)

In columns (1) to (5) record the corresponding estimations of coefficients β on MS from the regression $Illiquidity_{it} = \alpha + \beta \times MS_{it} + \boldsymbol{\gamma} \times \boldsymbol{X_{it}} + \varepsilon_{it}$ 180 days before and after the first to fifth event according to **Table 2**. The regression is cross-sectional that include all eligible stocks and matched ineligible stocks while controlled for firm level fixed effect and is repeated on a daily basis. Columns (6) lists the estimation of average of coefficients β from all five events. Results in Panel A are the estimations using relative effect spread as illiquidity and results in Panel B use Amihud's Illiquid Ratio as illiquidity measure.

occur in the same direction in both before and after the event date. However, the coefficients increase by 1.08% and 0.09% in the effective spread and price impact after qualifying the first 90 stocks for margin trading and short selling. This result is consistent with the findings of Sharif, Anderson, and Marshall (2014). They also use these 90 stocks from the Chinese stock market, matched them to cross-listed H-shares, and find that the liquidity of eligible stocks decreased after the first event. However, my finding is not statistically significant. In column (2), I listed results around the second event, where stocks eligible for margin-trading and short-selling have significantly lower spreads before and after the second event. Additionally, for the price impact measure, the impact is negative but insignificant after the event. The results for the first two events underline that the liquidity of eligible stocks declined relative to ineligible stocks after the events.

However, the third, fourth, and fifth events show different results. In Panel A, 180 days before the event date, the coefficients on MS are positive for third, fourth, and fifth events. Then, after each event, the coefficients become negative, which suggests that stocks eligible for margin-trading and short-selling would have higher liquidity. The differences are all positive and statistically significant, which implies the liquidity of eligible stocks improved after bans on margin-trading and short-selling were lifted. In Panel B, the effects of lifting bans on price impact are not as apparent as the one in Panel A. The difference in the third, fourth, and fifth events are all positive and two of them are statistically significant at the 1% level, suggesting a decrease in price impact of the eligible stock after bans were lifted. Though the differences for the first two events are negative, column (6) shows that the overall differences are positive and significant, suggesting that lifting bans would improve liquidities of eligible stocks compared to corresponding matched eligible stocks.

6.5 Impacts of Margin-trading and Short-selling

The previous sections suggest that stocks eligible for margin-trading and short-selling are more likely to have higher liquidity. Moreover, the event study proves the impact of lifting bans on margin-trading and short-selling improves eligible stock's liquidity. However, I only focus on the eligibility of margin-trading and short-selling by solely using one dummy variable that indicates the eligibility status. Therefore, in this section, I focus on the trading behaviour of these two activities by using the sample that only contains stocks eligible for margin-trading and short-selling. The sample period is still from March 31, 2010 to December 11, 2016. To accurately capture the behaviour of margin-trading and short-selling, I use two variables that measure their respective trading activities. The regression has the following specifications:

$$Illiquidity_{it} = \alpha + \beta_1 \times Relative\,Finance\,Interest_{it} + \beta_2 \times Relaative\,Short\,Interest_{it} + \gamma \times \boldsymbol{X_{it}} + \varepsilon_{it} \qquad (3)$$

where Illiquidity$_{it}$ is the illiquidity measure; α is the constant of the regression; Relative Finance Interest$_{it}$ and Relative Short Interest$_{it}$ are independent variables that measure the margin-trading and short-selling positions (definitions are indicated in Section 4.4); β_1 and β_2 are coefficients on these two variables; γ is a constant vector and $\boldsymbol{X_{jt}}$ is a vector containing control variables; and ε_{ijt} is the error term. In this panel regression, I also control for both day fixed effect and firm fixed effect. **Table 19** shows estimates of regressions with and without control variables. In columns (1) and (3), coefficients on both independent variables are statistically significant and negative, suggesting that both margin-trading and short-selling activities would improve the liquidities of stocks when excluding control variables. However, after controlling for the trading activities and firm characteristics that would influence the stock's liquidity, the impact of short-selling becomes the opposite. Both of the results from columns (2) and (4) imply that a higher position in margin-trading would lower both the effective spread and price impact while a higher position in short-selling is associated with an increase in the spread and price impact, which hinders liquidity. This negative impact of short-selling on liquidity is consistent with the findings of Ma et al. (2018) but inconsistent with that of Li et al.'s

Table 19. Panel Regressions: Relative Effective Spread, Amihud's Illiquid Ratio and Relative Finance Interest and Relative Short Interest

VARIABLES	(1) Relative Effective Spread	(2) Relative Effective Spread	(3) Amihud's Illiquid	(4) Amihud's Illiquid
Relative Finance	-0.659***	-0.925***	-2.235***	-1.521***
Interest	(0.0956)	(0.0831)	(0.314)	(0.153)
Relative Short	-66.04***	31.96***	-393.2***	74.39***
Interest	(13.50)	(11.61)	(40.94)	(17.96)
Price		-0.224***		-0.0376**
		(0.0153)		(0.0164)
Firm Size		-0.0943***		-0.319***
		(0.0122)		(0.0264)
Volume		-0.0432***		-0.574***
		(0.00253)		(0.00704)
Volatility		0.0709***		0.127***
		(0.00377)		(0.0107)
Ownership		-0.00849**		-0.0159**
Concentration		(0.00392)		(0.00630)
Return		0.684***		-0.130
		(0.0324)		(0.171)
HS300		0.0268***		0.0353***
		(0.00677)		(0.0133)
Price Limit		0.0672***		0.767***
		(0.0143)		(0.0340)
AR(1)	0.450***	0.323***	0.188***	0.0276***
	(0.00903)	(0.00700)	(0.00517)	(0.00286)
Constant	-3.583***	-1.176***	-18.84***	-5.847***
	(0.0595)	(0.179)	(0.121)	(0.354)
Observations	702,987	701,009	702,987	701,009
R-squared	0.691	0.719	0.516	0.594

There are two dependent variables: the Relative Effective Spread and Amihud's Illiquid Ratio, both on daily basis. These variables are taken logarithm form so that their distributions are more likely to be normal. Relative Finance interest is the ratio of the number of shares that borrowed yet not repaid to the total number of shares outstanding. Relative Short interest is the ratio of the number of stocks that be shorted but not repurchased to the total number of shares outstanding. Price, Firm size, Volume, Turnover, Voaltility and Ownership Concentration are also in logarithm. Because the liquidity is considered to correlate with itself, the AR(1) is the one lag of the dependent variable with a lag time of one day. More specifically, AR(1) represents the lagged relative effective spread, lagged Amihud's Illiquid Ratio. All regressions are controlled for the time fixed effect and firm fixed effect as for every day and every stock, one daily dummy variable and one firm dummy variable are included in the regression. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

(2018). The impacts of control variables are most consistent with the literature mentioned in Chapter 5. Price, volume, and firm size are negatively associated with illiquidity measures while volatility is positively associated. Moreover, the price limit is positively correlated to both illiquidity measures. However, the impact of ownership concentration becomes different compared to the results in Section 6.3. This suggests that for stocks that are eligible for margin-trading and short-selling, higher concentrated ownership seems to improve the stock's liquidity. Additionally, the coefficient's sign in HS300 also changes compared to the previous regression results, which could simply be caused by the sample changes.I use finance turnover and short turnover to measure the margin-trading and short-selling activities (definitions are itemized in Section 4.4). As mentioned in Chapter 4, these variables are different from finance interest and short interest since they capture the daily trading activities of margin-trading and short-selling. On the other hand, relative values of the finance interest and short interest measure the position of margin-trading and short-selling. To further test the impact of margin-trading and short-selling activities on a stock's liquidity, I run a regression with the following specifications:

$$Illiquidity_{it} = \alpha + \beta_1 \times Finance\,Turnover_{it} + \beta_2 \times Short\,Turnover_{it} + \gamma \times \boldsymbol{X_{it}} + \varepsilon_{it} \quad (4)$$

This equation is significantly similar to equation (3). The only difference is the changes in the independent variables. The results are shown in **Table 20**. When control variables are not considered, the impacts of finance turnover on both effective spread and price impact are not significant. While short turnover seems only to decrease the effective spread, it does not do so towards the price impact. However, after including control variables, the effects of margin-trading and short-selling activities become well defined. Columns (2) and (4) illustrate that increased trade in margin-trading activities would lower the illiquidity measures, which then improves the liquidity. In contrast, short turnovers are positively associated with both illiquidity measures, which infers that an increase in short-selling trading would impair a stock's liquidity. Consistent with literature and previous results, trading activities like price and volume are negatively associated with spread and price impact while volatility is positively associated. Firm size is

Table 20. Panel Regressions: Relative Effective Spread, Amihud's Illiquid Ratio and Finance Turnover and Short Turnover

VARIABLES	(1) Relative Effective Spread	(2) Relative Effective Spread	(3) Amihud's Illiquid	(4) Amihud's Illiquid
Finance Turnover	-0.0220	-0.132***	-0.0340	-0.514***
	(0.0196)	(0.0169)	(0.0651)	(0.0412)
Short Turnover	-0.367***	0.0563*	0.694	2.391***
	(0.116)	(0.0292)	(0.463)	(0.326)
Price		-0.229***		-0.0926***
		(0.0157)		(0.0211)
Firm Size		-0.113***		-0.414***
		(0.0136)		(0.0360)
Volume		-0.0180***		-0.498***
		(0.00268)		(0.0103)
Volatility		0.0535***		0.217***
		(0.00384)		(0.0133)
Ownership Concentration		0.00503		0.00179
		(0.00377)		(0.00713)
Return		-0.113**		2.044***
		(0.0476)		(0.601)
HS300		0.0167**		0.00342
		(0.00664)		(0.0147)
Price Limit		0.0578***		0.817***
		(0.0146)		(0.0379)
AR(1)	0.455***	0.330***	0.194***	0.0374***
	(0.00913)	(0.00716)	(0.00528)	(0.00289)
Constant	-3.588***	-1.415***	-18.86***	-5.075***
	(0.0601)	(0.193)	(0.123)	(0.468)
Observations	702,987	701,006	702,987	701,006
R-squared	0.690	0.717	0.514	0.578

There are two dependent variables: the Relative Effective Spread and Amihud's Illiquid Ratio, both on daily basis. These variables are taken logarithm form so that their distributions are more likely to be normal. Finance Turnover is the ratio of volume of shares being margin-borrowed to the total trading volume. Short Turnover is the ratio of volume of stocks being shorted to the total trading volume. Price, Firm size, Volume, Turnover, Voaltility and Ownership Concentration are also in logarithm. Because the liquidity is considered to correlate with itself, the AR(1) is the one lag of the dependent variable with a lag time of one day. More specifically, AR(1) represents the lagged relative effective spread, lagged Amihud's Illiquid Ratio. All regressions are controlled for the time fixed effect and firm fixed effect as for every day and every stock, one daily dummy variable and one firm dummy variable are included in the regression. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

also negatively correlated to both illiquidity measures. Moreover, the coefficient on price limit is positive as before. In this regression, the impacts of ownership concentration are unclear, and the impact of listing in HS300 is similar to the last regression.

6.6 Further Analysis

6.6.1 Mechanism Analysis

In the previous section, I find that margin-trading improves liquidity while short-selling hampers stocks' liquidity. As mentioned in Ma et al.'s (2018) study, both margin-trading and short-selling activities seem to increase the trading activity. Hence, both should lead to an improvement in liquidity. Moreover, according to Diamond and Verrecchia's (1987) model, short-selling could help incorporate new information into stock prices, which in turn increases the liquidity. Although the impact of margin trading on liquidity is comprehensible, the impact of short-selling on reducing liquidity requires further analysis.

In this paper, I assume that short selling could reduce stock liquidity since short sellers are informed traders and increase risks associated with adverse selection of the uninformed traders. According to Cai et al. (2013), short-sellers are most likely to be informed traders who would deter other non-informed traders from trading the stock. Therefore, stocks that have more short-sellers would attract less uninformed traders since the latter would rather trade other stocks. Consequently, this leaves stocks with high short-selling behaviour with less liquidity. Ultimately, short-selling activities reduce liquidity because short-sellers are primarily informed traders.

In this section, I will test the hypothesis on whether short-sellers are informed traders. Previous empirical research (Engelberg et al., 2012; Kolasinski et al., 2013; Chang et al., 2014; Akbas et al., 2017) suggests that short-sellers are essentially informed traders who could predict future returns. Chang et al. (2014) suggest that short-selling in the Chinese stock market is more likely to be an informed activity and has predictive power on future returns. To test this hypothesis, I begin with the following regression that evaluates whether the changes in the margin-trading and short-selling positions could predict future returns. I utilize the returns on future day t+2 instead of t+1 to avoid any reversal effect.

$$Return_{it+2} = \alpha + \beta_1 \times \Delta margin_{it} + \beta_2 \times \Delta short_{it} + \gamma \times X_{it} + \varepsilon_{it} \quad (5)$$

where $Return_{it+2}$ is the return of stock i on day t+2; $\Delta margin_{it}$ is the change in relative finance interest of stock i on day t and $\Delta short_{it}$ is change in relative short interest of stock i on day t; $\boldsymbol{X_{jt}}$ is a vector of control variables that include determinants of liquidity, past return, and turnover. This regression also controls for both firm fixed

Table 21. Can Change in Margin and Short Predict Future Return

	Model (1)	Model (2)	Model (3)
Δmargin	-0.0284 (0.0528)	0.0180 (0.0557)	0.00648 (0.0567)
Δshort	-2.317*** (0.891)	-2.709*** (0.909)	-2.262** (0.897)
Return (1-5)		-0.0237 (0.0176)	-0.0148 (0.0178)
Turnover (1-5)		-0.000345* (0.000205)	0.000114 (0.000275)
Price			-0.000292 (0.000298)
Firm Size			-0.00411*** (0.000452)
Volume			-0.000455* (0.000270)
Volatility			0.000827** (0.000322)
Ownership Concentration			-0.000305* (0.000161)
HS300			0.000803 (0.000505)
Price Limit			-0.000263 (0.00165)
Constant	0.000718*** (5.87×10^{-06})	-0.000772 (0.000886)	0.0830*** (0.00633)
Observations	793,512	776,156	774,394
Adjusted R^2	0.476	0.480	0.481

Dependent variable is future return on day t+2. Δ margin is changes in relative finance interest (=relative finance $interest_{it}$-relative finance $interest_{it-1}$) and Δ short is changes in relative short interest (=relative short $interest_{it}$-relative short $interest_{it-1}$). Because the return is considered to correlated with itself, Return (1-5) is the average return of past five days and Turnover (1-5) is the average turnover of past five days. Price, Firm size, Volume, Voaltility and Ownership Concentration are also in logarithm. All regressions are controlled for the time fixed effect and firm fixed effect as for every day and every stock, one daily dummy variable and one firm dummy variable are included in the regression. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

and day fixed effect. The results are presented in **Table 21**.

In column (1), I only include two independent variables, namely the changes in the margin and changes in short. Coefficients imply that changes in the position of margin-trading have an insignificant impact on future returns while changes in a short-selling position could predict negative future returns. Since there is always autocorrelation in returns that depend on past trading activities, I add two control variables in column (2) to control for the impact of weekly return reversal and turnover. $Return(1\text{-}5)_{it}$ is the average return of the past 5 days while $Turnover(1\text{-}5)_{it}$ is the average turnover of the past 5 days for stock i at time t. After controlling for past return and turnover, Δshort remains negatively associated with a future return while Δmargin still has no predictive power. However, the average of past returns seems to have no significant impact on future returns while an increase in past turnover could partly predict a lower future return. In column (3), I added more control variables that include those used in previous sections like price and firm size where changes in short-selling position remain negatively correlated to a future return. The outcomes suggest that an increase of 1% in relative short interest would lead to a 2.26% decrease in the stock's return. On the contrary, changes in margin-trading position would not influence the stock's future return. Results from these 3 models are consistent with the existing literature, such as Engelberg et al., 2012 who are arguing that short-sellers are informed traders. Moreover, the results also support the finding of Chang et al. (2014) that margin-trading investors could not predict future returns in the Chinese stock market.

To further test the hypothesis that short-selling reduces the stock's liquidity because of adverse selection, I assume that in firms with higher information asymmetry, short-selling would have a more substantial impact on liquidity than in firms with less information asymmetry. At this point, I divide the sample into three groups (Group 1, Group 2, and Group 3) and construct two dummy variables (Group 2 and Group 3). Each group contains stocks with different levels of information asymmetry. Firm size, institutional ownership, and the number of analysts' reports are respectively used as proxies for levels of information asymmetry. I include stocks with high information asymmetry in Group 1 and stocks with a low level of information asymmetry in Group 3. The regression is shown in the following equation:

$$Illiquidity_{it} = \alpha + \beta_1 \times Finance\,Turnover_{it} + \beta_2 \times Group2_{it} \times Finance\,Turnover_{it} + \beta_3 \times Group3_{it} \times Finance\,Turnover_{it} + \theta_1 \times Short\,Turnover_{it} + \theta_2 \times Group2_{it} \times Short\,Turnover_{it} + \theta_3 \times Group3_{it} \times Short\,Turnover_{it} + \gamma \times X_{it} + \varepsilon_{it} \qquad (6)$$

$Illiquidity_{it}$ is the illiquidity measures that include the relative effective spread and Amihud's Illiquid Ratio of stock *i* on day *t*; Finance Turnover and Short Turnover are measures of margin-trading and short-selling activities respectively; β_1 is the coefficient on Finance Turnover that represents the impact of margin-trading activity on liquidity in stocks with highest information asymmetry; β_2 is the coefficient on the term $Group2_{it} \times Finance\,Turnover_{it}$ that represents the differential impact of margin-trading on stocks with a medium level of information asymmetry (stocks in Group 2) relative to Group 1 stocks; β_3 is the coefficient on the term $Group3_{it} \times Finance\,Turnover_{it}$ that represents the differential impact of margin-trading on stocks with the highest levels of information asymmetry (stocks in Group 3) relative to Group 1 stocks. Similarly, θ_1 shows the impact of short-selling activities on liquidity in stocks with the highest levels of information asymmetry (stocks in Group 1) while θ_2 and θ_3 represent the differential impact of short-selling activity on

Table 22. Information Asymmetry and Impacts of Finance Turnover and Short Turnover

	Panel A. Relative Effective Spread			Panel B. Amihud's Illiquid Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
	Firm size	Institutional Holding	No. of analyst reports	Firm size	Institutional Holding	No. of analyst reports
β_1	-0.0323	0.0149	-0.0304*	-0.374***	-0.331***	-0.390***
	(0.0212)	(0.0207)	(0.0177)	(0.0458)	(0.0514)	(0.0447)
θ_1	0.662***	0.251**	0.842***	4.404***	2.481***	2.189***
	(0.179)	(0.122)	(0.102)	(0.689)	(0.431)	(0.382)
β_2	-0.156***	-0.0772***	-0.152***	-0.271***	-0.229***	-0.211***
	(0.0310)	(0.0299)	(0.0238)	(0.0631)	(0.0651)	(0.0573)
β_3	-0.164***	-0.329***	-0.309***	-0.201**	-0.228***	-0.269***
	(0.0365)	(0.0317)	(0.0302)	(0.0809)	(0.0743)	(0.0779)
θ_2	-0.531**	-0.178	-0.140	-0.900	0.195	0.378
	(0.224)	(0.156)	(0.119)	(0.674)	(0.435)	(0.335)
θ_3	-0.524**	-0.396**	0.109	-1.823**	-0.117	0.755
	(0.214)	(0.201)	(0.154)	(0.726)	(0.561)	(0.470)
$\beta_1 + \beta_2$	-0.189***	-0.0623**	-0.182***	-0.645***	-0.560***	-0.600***
	(0.0246)	(0.0243)	(0.0239)	(0.0563)	(0.0551)	(0.0578)
$\beta_1 + \beta_3$	-0.196***	-0.314***	-0.340***	-0.575***	-0.559***	-0.658***
	(0.0301)	(0.0254)	(0.0283)	(0.0717)	(0.0622)	(0.0757)
$\theta_1 + \theta_2$	0.130	0.0723	-0.0562	3.504***	2.676***	2.567***
	(0.143)	(0.113)	(0.117)	(0.426)	(0.400)	(0.365)
$\theta_1 + \theta_3$	0.138	-0.146	0.193	2.581***	2.364***	2.945***
	(0.119)	(0.171)	(0.146)	(0.370)	(0.480)	(0.445)
Observations	700,879	700,879	700,879	700,879	700,879	700,879
Adjusted R^2	0.727	0.731	0.723	0.587	0.585	0.584

Dependent variables are relative effective spread (in Panel A) and Amihud's Illiquid Ratio (in Panel B). In columns (1) and (4), firm size is used as measure of information asymmetry level. In columns (2) and (5), institutional shareholding ratio is used as measure of information asymmetry level. In columns (3) and (6), number of analysts' reports is used as measure of information asymmetry level. Control variables include price, firm size, volume, volatility, ownership concentration, HS300 dummy variable and price limit dummy variable. Estimates of control variables are not showed in this table. All regressions are controlled for the time fixed effect and firm fixed effect as for every day and every stock, one daily dummy variable and one firm dummy variable are included in the regression. β_1 and θ_1 represent the impact of margin-trading activity and short-selling on liquidity in stocks with highest information asymmetry (stocks in Group 1); β_2 and β_3 represent the differential impact of margin-trading on stocks with median and highest information asymmetry (stocks in Group 2 and Group 3). θ_2 and θ_3 represent the differential impact of short-selling activity on stocks median (Group 2) and highest (Group 3) information asymmetry. $\beta_1 + \beta_2$ is the marginal effect of margin-trading on liquidity of stocks in Group 2; $\beta_1 + \beta_3$ is the marginal effect of margin-trading on liquidity of stocks in Group 3; $\theta_1 + \theta_2$ is the marginal effect of short-selling on liquidity of stocks in Group 2 and $\theta_1 + \theta_3$ is the marginal effect of short-selling on liquidity of stocks in Group 3.The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

stocks with medium (Group 2) and highest (Group 3) levels of information asymmetry. Apart from these coefficients, I also focus on the marginal effect of

margin-trading and short-selling on liquidities. More specifically, $\beta_1 + \beta_2$ ($\theta_1 + \theta_2$) is the marginal effect of margin-trading (short-selling) on the liquidity of stocks in Group 2 while
$\beta_1 + \beta_3$ ($\theta_1 + \theta_3$) is the marginal effect of margin-trading (short-selling) on the liquidity of stocks in Group 3. The control variables $\mathbf{X_{it}}$ are the same ones used in equations 1, 2, and 3. Like in the previous regressions, I also controlled for both the firm fixed effect and day fixed effect in this regression.

In **Table 22** columns (1) and (4), firm size is used to capture the level of information asymmetry and the sample are classified into three groups with the differential level of information asymmetry. Stocks in Group 1 are stocks with small firm size with less than two-thirds of other stocks while stocks in Group 3 are those that have a large firm size with higher than two-thirds of other stocks. The remaining one-third of stocks with medium sizes are in Group 2. The coefficients β_1 for both illiquidity measures are negative but insignificant for effective spread while coefficients θ_1 are both positive and statistically significant. This implies that finance turnover improves liquidity while short turnover decreases the liquidity of stocks in Group 1. It is also found that both coefficients β_2 and β_3 are all negative for both illiquidity measures. Also, both coefficients θ_2 and θ_3 are negative but θ_2 for price impact is not significant. However, to determine the marginal impact of margin-trading and short-selling on liquidities for Groups 2 and 3, it is vital to focus on the sum of coefficients. $\beta_1 + \beta_2$ and $\beta_1 + \beta_3$ show the marginal effect of finance turnover on the stock liquidity of Groups 2 and 3. All the results are negative and statistically significant, implying that margin-trading improves the liquidity of stocks in Groups 2 and 3. In contrast, $\theta_1 + \theta_2$ and $\theta_1 + \theta_3$ are not significant for effective spread. This suggests that the impact of short-selling activity is not statistically significant on the liquidity for stocks with medium and high levels of information asymmetry. However, the results from price impact recommend that the marginal effects of short-selling on liquidity for stocks in Groups 2 and 3 are 3.504 and 2.581, which is less than the effect in Group 1 (θ_1 = 4.404), which suggests that Group 1 stocks have the highest price impact, thus lowest liquidity. Overall, when utilizing firm size as a measure of information asymmetry, the results underline that short-selling has the most substantial negative impact on both illiquidity measures in the group of stocks with the highest level of information asymmetry.

In columns (2) and (5), I present the coefficients using the institutional share-holding ratio as a proxy for the level of information asymmetry. I equally divide the stocks into three groups according to their institutional shareholding rate. Stocks with low institutional holding ratios are in Group 1. The coefficients β_1 for price impact are negative and significant. However, for effective spread, these coefficients are not significant. The θ_1 is both positive and statistically significant. This denotes that finance turnover improves price impact while short turnover decreases the liquidity of stocks with high levels of information asymmetry. Furthermore, the outcomes highlight that both coefficients β_2 and β_3 are all negative for both illiquidity measures. Coefficients θ_2 for effective spread are negative and θ_3 in columns (2) and (5) are also negative. However, most of them are not statistically significant. The sum of coefficients $\beta_1 + \beta_2$ and $\beta_1 + \beta_3$, which show the marginal effect of finance turnover on the stocks' liquidity of Groups 2 and 3 are negative. This signifies that margin-trading still improves the liquidity of stocks in Groups 2 and 3. Both $\theta_1 + \theta_2$ and $\theta_1 + \theta_3$ are insignificant for effective spread. By using the effective spread as a measure for stocks with medium and high levels of information asymmetry, this implies that the impact of short-selling activity on liquidity is insignificant. However, $\theta_1 + \theta_2$ in column (5) is higher than θ_1, indicating that short-selling in stocks with a medium institutional shareholding ratio would have the strongest negative effect on price impact. Overall results suggest that short-selling activities would have a negative impact on effective spread only in those stocks with the lowest institutional shareholding ratio and have the highest levels of information asymmetry.

In columns (3) and (6), when using thw number of analysts' reports as a proxy for the level of information asymmetry, results are notably similar to the previous ones. Both β_1 and θ_1 suggest that margin-trading improves liquidity while short-selling does otherwise. Coefficients $\beta_1 + \beta_2$ and $\beta_1 + \beta_3$ are all statistically significant and positive, which highlights that margin-trading could also improve the liquidities of stocks with medium and low levels of information asymmetry. The insignificant $\theta_1 + \theta_2$ and $\theta_1 + \theta_3$ of effective spread proves that for stocks with medium and low levels of information asymmetry, short-selling seems to have an insignificant effect. However, in column (6), both $\theta_1 + \theta_2$ and $\theta_1 + \theta_3$ are positive and statistically significant and are larger than θ_1. This indicates that short-selling would decrease liquidity the most in stocks with the highest number of analyst reports. In summary, the marginal impact of short-selling in Groups 2 and 3 vary across different measures of illiquidity. Short-selling in stocks with the highest levels of information asymmetry would have the strongest and significant negative impact on effective spread while short-selling increases price impact the most in stocks with the highest level of information asymmetry.

Despite the discrepancy in the last measure of information asymmetry, results from **Tables 21** and **22** support the hypothesis that short-sellers are informed traders. First, their positions have a predictive power of returns that margin-traders do not possess. The trading behavior of short sellers would deter other uninformed investors from trading the stocks. Having said this, in stocks with the highest levels of information asymmetry, short-selling tends to have the strongest negative impact on liquidity, especially when using the effective spread as a measure of illiquidity.

6.6.2 Influences from Market Conditions

In this section, I further investigate the impact of margin-trading and short-selling on liquidity under poor market conditions. Several researchers, such as Beber and Pagano (2013) argue that a short-sale ban during the financial crisis actually hinders the market's liquidity. However, the regulators still believe that short-selling would decrease a stock's liquidity. Moreover, the impact of margin-trading on liquidity during a crisis seems to be different compared to operations in a normal market condition. Brunnermeier and Pedersen (2009) explain that when stocks have large losses, the impact of funding liquidity and stocks' liquidities would spiral to the point that both would dry up and further impair the other. Kahraman and Tookes (2017) confirmed this empirically using data from the Indian stock market. Margin-trading would decrease liquidity during a crisis period rather than improve as it does during the normal period.

To investigate whether the impacts of margin-trading and short-selling on liquidity are different during the crisis period, I separate the sample into two parts, one with a poor market condition and the other that contains the rest. One dummy variable called "Downturn" is used to represent the market state, such as whether it is in poor condition or not. My method involves two ways to define this dummy variable: (1) Downturn is equal to one if the index return is less than 20th percentile and (2) Downturn is equal to one if index return is less than negative five per cent.

I first examine whether market conditions would change the impact of eligibility on liquidity. Following equation 1 and after adding the dummy variable Downturn, the regression will have the following specifications:

$$Iliquidity_{it} = \alpha + \beta_1 \times MS_{it} + \beta_2 \times MS_{it} \times Downturn_{it} + \gamma \times X_{it} + \varepsilon_{it} \qquad (7)$$

β_1 is the coefficient on eligibility MS and represents the impact of MS when the market is in a normal condition; $\beta_1 + \beta_2$ then represent the marginal effect of MS when the market is in poor condition; and $\mathbf{X_{it}}$ is a vector that includes all control variables used in previous regressions. The results are shown in **Table 23**.

In Panel A, the dummy variable is initially defined as equal to one when the index return is less than the 20th percentile. Using both illiquid measures, β_1 coefficients are negative and statistically significant. This is consistent with the results in **Table 23** that stocks eligible for margin-trading and short-selling would have lower spread and price impact, thus have higher liquidity. The same result still holds in Panel B as Downturn is defined in a second way, which is equal to one when the index return is less than -5%. β_1 in Panels A and B prove that being eligible for margin-trading and short-selling could improve liquidity in overall sample period and sample period when market performance is in either a normal or good state. All coefficients of β_2 are positive and statistically significant while the coefficients of $\beta_1 + \beta_2$ are all positive where most of them are significantly different from zero. This result infers that when market performance is poor, especially when the index return is extremely at low levels, the stocks eligible for margin-trading and

Table 23. Poor Market Condition and Impact of Eligibility on Liquidity

	Panel A Downturn=1 if index return < 20^{th} percentile		Panel B Downturn=1 if index return < -5%	
	(1)	(2)	(3)	(4)
	Relative Effective Spread	Amihud's Illiquid Ratio	Relative Effective Spread	Amihud's Illiquid Ratio
β_1	-0.0205***	-0.0582***	-0.0170***	-0.0305***
	(0.00357)	(0.00763)	(0.00355)	(0.00744)
β_2	0.0213***	0.110***	0.0523***	0.157***
	(0.00316)	(0.0104)	(0.0186)	(0.0179)
$\beta_1 + \beta_2$	0.000858	0.05140***	0.03526**	0.12655***
	(0.00444)	(0.01011)	(0.01892)	(0.01838)
Observations	1,362,391	1,362,391	1,362,391	1,362,391
R-squared	0.719	0.616	0.719	0.587

Dependent variables are relative effective spread (in columns (1) and (3)) and Amihud's Illiquid Ratio (in columns (2) and (4)). In Panel A, downturn is defined equals to one when the index return is less than its 20^{th} percentile. In Panel B, downturn is defined equals to one when the market index return is less than minus five percent. Independent variable is MS, a dummy variable equals to one if a stock is eligible for margin-trading and short-selling on particular day. Control variables include price, firm size, volume, volatility, ownership concentration, HS300 dummy variable and price limit dummy variable. Estimates of control variables are not showed in this table. All regressions are controlled for the time fixed effect and firm fixed effect as for every day and every stock, one daily dummy variable and one firm dummy variable are included in the regression. β_1 represent the impact of MS on liquidity when market is not under poor condition; β_2 is the differential impact of MS on liquidity when market is under poor condition. $\beta_1 + \beta_2$ is the marginal effect of MS on liquidity when market is under poor performance. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

short-selling would have lower liquidity than ineligible stocks.

Since the impact of eligibility on liquidity changes in poor market conditions, I proceed to investigate whether the impact of margin-trading and short-selling activities on liquidity would change under poor market conditions or not. The regression takes place in the following form:

$$Liquidity_{it} = \alpha + \beta_1 \times Finance\ Turnover_{it} + \beta_2 \times Finance\ Turnover \times Downturn_{it} + \theta_1 \times Short\ Turnover_{it} + \theta_2 \times Short\ Turnover \times Downturn_{it} + \gamma \times X_{it} + \varepsilon_{it} \qquad (8)$$

Coefficients β_1 and θ_1 represent the impact of margin-trading and short-selling activities when the market is in a normal or good condition. The sum of coefficients $\beta_1 + \beta_2$ and $\theta_1 + \theta_2$ then represent the marginal effect of margin-trading and short-selling activities when the market is in poor conditions.

Table 24. Poor Market Condition and Impact of Margin-trading and Short-selling on Liquidity

	Panel A Downturn=1 if index return < 20th percentile		Panel B Downturn=1 if index return < -5%	
	(1)	(2)	(3)	(4)
	Effective Spread	Amihud's Illiquid	Effective Spread	Amihud's Illiquid
β_1	-0.127***	-0.525***	-0.129***	-0.530***
	(0.0171)	(0.0414)	(0.0170)	(0.0414)
θ_1	0.0662	2.399***	0.2775***	2.285***
	(0.0915)	(0.327)	(0.0911)	(0.326)
β_2	0.262**	1.099***	0.433***	1.094***
	(0.102)	(0.0939)	(0.0915)	(0.138)
θ_2	-0.985**	-7.931***	-1.053*	-5.920***
	(0.439)	(0.655)	(0.559)	(1.050)
$\beta_1 + \beta_2$	0.134	0.574***	0.304	0.564***
	(0.104)	(0.0848)	(0.494)	(0.132)
$\theta_1 + \theta_2$	-0.919**	-5.532***	-0.976*	-3.635**
	(0.437)	(1.611)	(0.562)	(1.018)
Observations	689,596	689,596	689,596	689,596
R-squared	0.718	0.580	0.718	0.582

Dependent variables are relative effective spread (in columns (1) and (3)) and Amihud's Illiquid Ratio (in columns (2) and (4)). In Panel A, downturn is defined equals to one when the index return is less than its 20th percentile. In Panel B, downturn is defined equals to one when the market index return is less than minus five percent. Dependent variables are finance turnover (the ratio of volume of shares being margin-borrowed to the total trading volume) and short turnover (the ratio of volume of stocks being shorted to the total trading volume). Control variables include price, firm size, volume, volatility, ownership concentration, HS300 dummy variable and price limit dummy variable. Estimates of control variables are not showed in this table. All regressions are controlled for the time fixed effect and firm fixed effect as for every day and every stock, one daily dummy variable and one firm dummy variable are included in the regression. β_1 and θ_1 represent the impact of margin-trading activity and short-selling on liquidity in stocks under normal market conditions; $\beta_1 + \beta_2$ is the marginal effect of margin-trading on liquidity of stocks under poor market condition; $\theta_1 + \theta_2$ is the marginal effect of short-selling on liquidity of stocks in crisis period. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

The related coefficients are shown in **Table 24**. Using both illiquid measures and definitions of poor market performance, the β_1 coefficients are all negative and statistically significant. This is consistent with the results in **Table 20** that highlight how margin-trading would improve liquidity. The θ_1 coefficients in Panels A and B are all positive but insignificant in column (1), which suggests that short-selling activities would decrease the liquidity. Generally, using the overall sample periods, the impacts of finance turnover and short turnover turn out to be the same when market performance is not at extremely poor levels. All coefficients of β_2 are positive and statistically significant while the coefficients of θ_2 are negative and significant in both panels that use both illiquidity measures. The coefficients of $\beta_1 + \beta_2$ are all positive but insignificant when using the effective spread as an illiquidity measure. This result infers that when the market performance is poor, the margin-trading activity would increase price impact. On the other hand, the coefficients of $\theta_1 + \theta_2$ are all negative and statistically different from zero in Panels A and B. This suggests that short-selling activity actually decreases the spread and price impact, which then improves a stock's liquidity when the market has extremely negative returns. This result is coherent with the prediction of Diamond and Verrecchia (1987). In their study, they expound on how constraints in short-sale would prevent the incorporation of negative information into the stock's price that hinders the price discovery process and decreases a stock's liquidity. In my case, when a market is in poor condition, information circulated in the market is more likely to be negative. Therefore, stocks that have a higher prevalence of short-selling activities integrate negative expectations into the price more rapidly, which then improves liquidity.

6.7 Conclusions

The overall results highlight that stocks eligible for margin-trading and short-selling could improve market liquidity. The robustness of the result becomes evident when using an event study. Moreover, I prove that margin-trading activities dominate the market, where its positioning and trading behavior simultaneously improve liquidity. In contrast, short-selling has detrimental impacts on liquidity given that I assume is caused by adverse selection. To support this hypothesis, I prove that changes in the short-selling position appear to predict future returns. Additionally, short-selling activities have the greatest negative impact on liquidities in stocks that have the highest levels of information asymmetry. In contrast, while changes in margin position have no predictive power of the returns, margin-trading activities have a stronger positive impact on liquidities of stocks with medium and low levels of information asymmetry. Furthermore, the results verify that stocks eligible for margin-trading and short-selling tend to have lower levels of liquidity during a market crisis period. The impacts of both activities also become opposite under poor market conditions. More specifically, increased margin-trading is associated with a higher price impact. This result is consistent with the findings of Kahraman and Tookes (2017) where margin-trading improves liquidity during a normal market period and decreases liquidity when under crisis. However, short-selling activities would improve liquidity when markets are not performing well. The result also partially supports the prediction of Diamond and Verrecchia (1987) that a short-sale ban would prevent the incorporation of negative information into the stock's price. When the market condition is poor or in crisis, stocks tend to deliver bad news rather than good. Therefore, short-sellers help disseminate negative information and incorporate it into the stock price. The improvement in price efficiency would become evident in the same way as liquidity. Generally, the findings attempt to explain the discrepancies between the governors' regulations and the theoretical and empirical findings from literature about the impact of short-sale bans during a financial crisis period. The governors believe that short-selling would be harmful to liquidity since its overall impact on liquidity is negative and short-sellers are more likely to be informed traders. On the other hand, the research findings on short-sale bans are also accurate given that these bans hinder the integration of information into the stock prices and ultimately lowers the liquidity during a market crash period.

CHAPTER 7: IMPACT OF MARGIN-TRADING AND SHORT-SELLING ON LEAD-LAG EFFECTS IN LIQUIDITY AND RETURN

7.1 Introduction

In 2015, the Chinese stock market encountered a severe market crisis from June 15 to mid-September. Before the crisis began, the stock market prices skyrocketed as the price of the Shanghai Composite Index rose by 150% in less than a year. Simultaneously, these events boosted leveraged trade, which includes margin-trading and short-selling. However, on June 15, 2015, after several large stocks plummeted, the prices of other median and small stocks also began to fall sharply. At the end of that day, over 1,000 stocks hit the lower price limit as their prices decreased by 10% compared to the closing prices from the previous trading day. In the following trading days, stock prices continued to decrease. From June 15 to September 13, 2015, there were a total of 16 out of 59 trading days, where over 1,000 stocks hit the lower price limit. Interestingly, it is observed that several large-cap stocks first hit the lower price limit, then other stocks followed this trend and hit the price limit. On one hand, as the regulators crackdown the most active speculators, the first round of selling takes place. Consequently, this leads to the financial loss of numerous speculators. Furthermore, this worsens the liquidity's state and the dropping of prices. Investors with high leverage need to address problems brought upon by huge margin calls that force them to liquidate their positions. As a result, prices drop even further and liquidity continues to decrease. On the other hand, markets in poor conditions make it tougher for leveraged-trading investors to raise the necessary capital to meet the margin requirement. In doing so, these investors will be forced to sell their other stocks that were not traded on leverage. The media believed that margin-trading caused these events to occur. As Richardson et al. (2017) argue, an aggregate negative shock in the ease of access to funding capital will cause highly invested and leveraged stocks to experience greater movements in returns. The media blamed high levels of leverage trading that led to stock return comovement, which ultimately caused the market to crash and the stock liquidity to dry up.

Many empirical studies already showed that leverage trading, including margin-trading and short-selling, could impact stocks' liquidities and price discoveries (e.g., Chang et al., 2007; Chang et al., 2014; Chen et al., 2016; Kahraman and Tookes, 2017). Results from Chapter 6 are also consistent with these literature, suggesting that margin-trading and short-selling would have impact on stock's liquidity. Moreover, many studies suggest that leverage trading could increase the comovements among stocks. Schinasi and Smith (2000) show that investors' leverage could help explaining the spread of shocks from one asset to the other. Brunnermeier and Pedersen (2009) further predict that losses on existing positions would pose constrains on funding liquidity, which further lead to the deleverage of other stocks, thus increases the liquidity commonality among various securities. Caccioli et al. (2014) demonstrate that the overlapping portfolios and leveraged investments could amplify contagions during the financial crisis period. These theoretical studies indicate that leverage trading have an impact on all stocks, not only those stocks that allowed for margin-trading and short-selling, also those ineligible stocks. However, very few empirical studies focus on investigating the lead-lag effect between leveraged stocks and un-leveraged stocks. In most equity markets (e.g. the U.S. market and the European markets), almost all stocks can be leverage traded during recent decades. Therefore, it is difficult to investigate the spillover effect of leveraged stocks. In contrast, only part of stocks in the Chinese stock markets are eligible for leverage trading (i.e. margin-trading and short-selling), while these eligible stocks change over time. This setting provides a perfect natural experiment that allows immediate investigation on the impact of investor leverage on liquidity and return spillover to other stocks. Taking advantage of unique market setting in the Chinese stock market, I will investigate the extent of how margin-trading and short-selling impact comovements in liquidity. In this chapter, I will focus on the comovements between stocks that are eligible and ineligible for leverage trading. More specifically, I will investigate how leverage trading contributes to the lead-lag in liquidity and lead-lag in return at the intraday level. As the literature documents these comovements on both daily and monthly bases, I will attempt to prove that those are formed at the intraday level, where eligible stocks would lead ineligible stocks in liquidity and return. Ultimately, my hypothesis states that stocks eligible for margin trading and short selling influence the liquidity and returns of ineligible stocks while the level of leveraged trading impacts the overall intraday lead-lag effect.

Actual market observations, along with the literature, help explain the formation of comovement in liquidity and returns. First, according to Brunnermeier and Pedersen’s (2009) theoretical analysis, leverage traders would face heavier funding constraints when the market drops. More specifically, they assume that investors hold two stocks, where one is an eligible stock where a trader uses leverage and the other is an ineligible stock without any leverage. When investors experience a price drop in the eligible stock, they have to either reduce the eligible stock's position or add capital to meet the margin requirements. If the investors choose the first option, they lose more money since they trade on leverage. Therefore, investors prefer the second choice that maintains their capital by selling ineligible stock. When the market crashes, it would be more difficult for margin-traders to raise capital and meet margin-call requirements. In turn, they will have to sell the other stocks that are not used for leverage trading. This would decrease the price of non-leveraged stocks, which leads to a decrease in liquidity of ineligible stocks. Even when investors lose money on both eligible and ineligible stocks, they would be more prone to trade ineligible stocks to satisfy the margin requirements. Moreover, according to Gromb and Vayanos's (2002) model, investors use leverage traded stock A as collateral to leverage the purchase of stock B. Then, a shock in stock A's price could lead to the forced deleveraging of stock A. Eventually, this causes the forced liquidation of stock B as the collateral's value decreases and fails to meet the margin requirement, especially when investors face constraints in funding liquidities. Therefore, stock trading with leverage on a given level will influence the lead-lag in liquidity and return. This is also known as the deleveraging channel that causes liquidity and returns lead-lag between eligible and ineligible stocks.

Apart from leverage trading, I also find other reasons that could help explain the lead-lag between eligible and ineligible stocks in liquidity and return. The second channel, the speed of information diffusion, is where stocks eligible for margin-trading and short-selling could influence the comovement in liquidity. Early studies like Lo and MacKinlay (1990) and many other studies (Hou and Moskowitz, 2005; Hou, 2007) find a lead-lag relationship between weekly returns of large-sized and small-sized stocks. They argue that the diffusion speed of market or industry-wide information on every stock causes this lead-lag relation. Stocks with larger firm sizes convey information at faster speeds, causing their prices to correspondingly react at a faster speed. In contrast, small-sized stocks incorporate information into the prices at a slower speed. As a result, researchers observe a lead-lag in returns between stocks with large and small firm sizes. Apart from the firm's size, institutional ownership also affects the lead-lag effect in returns, which is caused by the differences in speeds of information diffusion (Chan and Hameed, 2006). In the Chinese stock market, Chang et al. (2014) find that lifting bans on margin-trading and short-selling helps improve price efficiency and enable prices to incorporate more information. Additionally, Chen et al. (2016) find that prices of stocks allowed for margin-trading and short-selling become more efficient. Then, the intensity of margin-trading and short-selling are also positively associated with price efficiency, which suggests that margin-trading and short-selling assist the efficient incorporation of information into the stock prices. Recent research shows that the speed of information diffusion influences stock prices, leading to the lead-lag effect in stock returns. Therefore, I would argue that stocks eligible for margin-trading and short-selling could lead returns and possibly, the liquidity, of ineligible stocks. In summary, this "information diffusion speed" channel helps explain the lead-lag effect.

The third reason why eligible stocks could cause liquidity lead-lag in ineligible stocks is known as the "cross asset learning". According to Cespa and Foucault (2014), liquidity providers like institutional investors or fund managers are often informed about a certain stock from the prices of other stocks. Moreover, they argue that this cross asset learning process associates price informativeness and liquidity in self-reinforcing and positive ways, which causes a liquidity spillover. For example, if an investor holds stock A and learns information from stock B, a decrease in the liquidity of stock B will cause its price to become less informative. Consequently, the uncertainty of investors holding stock A increases, which further leads to the decrease in liquidity of stock A. Therefore, a small drop in the liquidity of one stock could result in a decrease of another and cause a lead-lag effect in liquidity. Chen et al. (2018) confirm this theory by highlighting the lead-lag effect in the liquidity between SPYs and E-minis during the financial crisis period. The decrease of liquidity in SPY leads to both liquidity drops in E-minis and an illiquidity contagion. In the Chinese stock market, stocks eligible for margin-trading and short-selling always have a large firm size, trading volume, and institutional shareholding, which are usually regarded as reference stocks like stock B in the previous example. Hence, liquidity changes in eligible stocks will affect ineligible stocks if the investors who hold ineligible stocks use eligible stocks as reference stocks. This reason is known as the “cross asset learning” channel.

Apart from liquidity, I argue that volatility, as a cardinal determinant of liquidity, could also influence the informativeness of the reference stocks. An increase in stock volatility implies that investors have more uncertainties about the price. As a measure of risk, volatility could reflect the price uncertainty from the investors’ point of view. For example, investors who hold one stock X could use the volatility in stock Y as a source of information related to the price changes in Y. An increase in stock Y’s volatility could be viewed as a decrease in the certainty of stock Y’s price. The drop in the price informativeness of stock Y leads to the uncertainty of holding stock X, which further leads to less trading of stock X. Consider investors like fund managers and institutional investors that hold several stocks, including eligible and ineligible stocks. If the volatility of eligible stocks increases, the informativeness about the stocks' prices decreases. Then, investors using eligible stocks as reference stocks would become reluctant to trade both eligible and ineligible stocks. Therefore, increases in the volatility of one stock could impact the price and liquidity of another. Following the "cross asset learning" theory, changes in volatility could be viewed as changes in the price informativeness.

Recent literature uses weekly or daily data to investigate the comovements in liquidities and returns (e.g. Lo and MacKinlay, 1990; Conrad, Gultekin, and Kaul, 1991; Fargher and Weigand, 1998; Hou and Moskowitz, 2005; Hou, 2007; Li et al., 2018). If comovements could be observed at the daily or weekly level, we should observe the lead-lag relation at the intraday level. In this chapter, I will utilise the intraday data to investigate the lead-lag effects in liquidities and returns from a micro perspective. This study seeks to contribute to the literature by expanding the understanding of how comovements in liquidity and return are formed through the intraday data. If there were comovements on a daily or weekly basis, using high-frequency minute data would be better to understand the evolution and formation of comovements. In this chapter, I find a strong lead-lag relation in liquidities and returns between stocks eligible and ineligible for leverage trading. More specifically, stocks eligible for margin-trading lead the liquidity and return of ineligible stocks. These lead-lag effects exist for individual stock analysis and under different market conditions. When using all eligible stocks as the portfolio and ineligible stocks as the other, there are also strong lead-lag relations in liquidity and returns between the eligible and ineligible portfolios of stocks. Further robustness test also proves that the lead-lag effects are not solely caused by the firm characteristic of eligible stocks. Using mediation analysis, I study the impact of leverage trading on lead-lag in liquidities and returns through different mediation channels. Over half of the impact is caused by the deleverage channel and one-third could be explained through cross asset learning. The speed of information diffusion is also a channel that helps explain the impact of leverage trading on lead-lag in liquidity and return.

7.2 Data Description and Methodology

In this section, I use the intraday data, including the 1-minute bid price, ask price, trading price, and the return and trading volumes to estimate the changes in liquidities and price discovery process during the day. In contrast with the daily data, this intraday, 1-minute frequency data could provide more details and accurate information about the dynamic in liquidities and the price discovery process between eligible and ineligible stocks, especially during specific market conditions. The sample period begins from September 22, 2014, when a total of 900 stocks were allowed for margin-trading and short-selling until a day before December 12, 2016, when the number of eligible stocks increased to 950. The sample period generally covers market conditions that are in steady, boosting, and crisis states. This section includes 900 sample stocks eligible for margin-trading and short-selling, along with the corresponding matched ineligible stocks.

The matching approach and criteria are the same ones from Section 6.2. I use industry, closing price, market capitalization, and daily trading volume as matching criteria. The prices, market capitalization, and trading volume of matched ineligible stocks have values that are closest to eligible stocks in the same industry. The summary statistics for matching pairs are listed in **Table 25**. In Panels A and B, I listed the summary statistics of three matching criteria for eligible and ineligible stocks. Eligible stocks have greater firm sizes and higher trading volumes. Additionally, the t-test results from Panel C show that eligible stocks tend to have higher prices, market capitalizations, and trading volumes than ineligible stocks. To control for this difference in matching results, in Section 7.5, I execute the robustness check. Then, for the regressions in Section 7.6, I include all three matching criteria as the control variables.

To investigate the lead-lag relation in liquidities between margin and non-margin stocks, I use the vector autoregression (VAR) method, which follows the methodology of Hou (2007). The VAR equations are as follows.

$$L_{M,i}(t) = a_{i,0} + a_{i,k}\sum_{k=1}^{K} L_{M,i}(t-k) + b_{i,k}\sum_{k=1}^{K} L_{N,i}(t-k) + e_{M,i}(t) \qquad (9)$$

$$L_{N,i}(t) = c_{i,0} + c_{i,k}\sum_{k=1}^{K} L_{M,i}(t-k) + d_{i,k}\sum_{k=1}^{K} L_{N,i}(t-k) + e_{N,i}(t) \qquad (10)$$

In Equation (9), the LHS is the liquidity of stocks eligible for margin-trading and short-selling (eligible stocks hereafter)[21]. While in Equation (10), the variable on the left is the liquidity of stocks ineligible for margin-trading or short-selling (ineligible stocks

[21]Eligible stocks refer to stocks eligible for margin-trading and short-selling while ineligible stocks are those stocks that are not eligible for margin-trading nor short-selling.

Table 25. Summary Statistics for Matched Pairs

	Mean	Median	Standard deviation	Minimum	Lower quantile	Upper quantile	Maximum
Panel A. Eligible stocks characteristic							
Price	17.57	13.88	13.58	1.92	8.82	21.95	261.21
Market Cap	2.48×10^{10}	1.32×10^{10}	5.17×10^{10}	1.17×10^{9}	7.95×10^{9}	2.43×10^{10}	2.21×10^{12}
Volume	5.05×10^{8}	2.62×10^{8}	8.41×10^{8}	2.46×10^{5}	1.30×10^{8}	5.55×10^{8}	3.79×10^{10}
Panel B. Matched ineligible stocks characteristic							
Price	17.55	13.89	13.52	2.15	8.83	21.93	273.46
Market Cap	9.71×10^{9}	8.02×10^{9}	7.47×10^{9}	4.07×10^{8}	5.65×10^{9}	1.14×10^{10}	3.45×10^{11}
Volume	3.47×10^{8}	2.17×10^{8}	4.92×10^{8}	2.09×10^{5}	1.15×10^{8}	4.14×10^{8}	2.41×10^{10}

Panel C. Difference between eligible and ineligible stocks

	Difference in Mean	T-statistic	Difference in Median	Z-score
Price	0.014***	10.32	-0.01	-1.207
Market Cap	1.51×10^{10}***	201.14	5.18×10^{9}***	468.37
Volume	1.58×10^{8}***	151.41	4.50×10^{7}***	226.58

In panel A and B, the summary statistics for three matching criteria for eligible stocks and corresponding matched ineligible stocks is showed. Price is the closing price in RMB; Market Cap is the stock's market capitalization (in RMB value), which equals to the total value of shares outstanding; Volume is the stock's trading volume, also in RMB value. All these characteristics are on daily basis. In panel C, the difference in mean and difference in median of three characteristic between eligible and matched ineligible are showed. T-statistic is for the null hypothesis that the difference in means equals to zero. Z-score is from a non-parametric Wilcoxon matched-pairs test of the null hypothesis that the difference in medians equals zero. Three (***) asterisks represent statistically significant at 1% level.

hereafter). Given the multiple stocks on different days, I assign an ID i to each pair on sample days[22] for the different pairs of stocks on different days. $L_{M,i}(t)$ is the margin stock's liquidity from the i^{th} pair at the t^{th} minute and $L_{N,i}(t)$ is the t^{th} minute's liquidity of non-margin stock from the i^{th} pair.The coefficient $a_{i,k}$ in equation 9 indicates the autocorrelation of eligible stock i's liquidities. Coefficient $b_{i,k}$ represents the extent of how an ineligible stock's liquidity would influence the liquidity of an eligible stock. In contrast, the coefficient $c_{i,k}$ measures how an eligible stock's liquidity would affect an ineligible stock's liquidity. The coefficient $d_{i,k}$ in equation 10 shows the autocorrelation in the ineligible stock's liquidities. To determine the lead-lag effect, I compare coefficient $b_{i,k}$ to $c_{i,k}$ and calculate the difference between $c_{i,k}$ and $b_{i,k}$ (i.e. $c - b$). If coefficient $c_{i,k}$ is larger than $b_{i,k}$, it suggests that the eligible stock leads the ineligible stock in liquidity.

In this chapter, we utilize the same liquidity measures (actually, they should be illiquidity measures)from the previous chapter, which are the relative effective spread and Amihud's Illiquid Ratio. In contrast to the last two chapters, both spread and price impact are calculated using high-frequency data. Therefore, I use following specifications to calculate the relative effective spread price impact on one-minute time interval.

$$Relative\ Effective\ Spread_t = 2 \cdot |\ln{(P_t)} - \ln{(M_t)}|$$

$$\mathrm{ILLQI}_t = \frac{|R_t|}{Vol_t}$$

where P_t is the trading price at the t^{th} minute; M_t is the mid-point price at the t^{th} minute, which is equal to half of the bid price and ask price at minute t; R_t is the t^{th} minute's return; and Vol_t is the total trading volume (in RMB value) during the t^{th}

[22] So for each pair of stocks on different days, it would have one specific ID number. For example, there are 850 pairs of stocks on day 1 that have the ID numbers from 1 to 850. Then, the 10th pair of stock on day 2 will have an ID number of 860.

minute.

To determine the number of lags used in the regression, I first calculate the daily Akaike information criterion (AIC) and Bayesian Information Criterion (BIC) for each pair of stocks. Both criteria suggest that using one lag would be the most appropriate. More specifically, since for nearly all pairs of stocks, the lowest AIC and BIC appear at one lag while both criteria increase with the number of lags. Then, I also run the augmented Dickey-Fuller test (ADF) to each pair of matched stocks to test for the unit roots. Since the result is significantly larger than the critical value, this suggests that there is no unit root and there is no need for the use of the difference in liquidity; instead, using liquidity will suffice. The results imply that there are no unit roots with one, five, or even ten lags. Therefore, as the AIC and BIC imply, it is natural to use only one lag in the regressions. Also, I include all five lags in the regressions to ensure that the information shock does not fully cause the lead-lag effects. An interval of five minutes is also widely used in technical analysis. I estimate both Equations (9) and (10) for each pair of stocks each day with one (K=1) and five (K=5) lags respectively.

The Chinese stock market has specific trading rules that impact price changes and trading activities. As mentioned in Chapter 5, one is the price limit rule, where the trading price on the current day can only increase or decrease by 10% of the closing price on the previous trading day. When the stock hits the price limit, the trading volume would suddenly drop, as the price can no longer be moved up or down anymore. After the stock hits the price limits, this trading rule causes the trading volume of several stocks to be maintained at very low levels or even become zero. Concurrently, the spreads are impossible to calculate since there is no bid or ask prices when hitting upward or downward limits. Therefore, if the stocks hit the price limit in a short time (e.g. less than 30 minutes), the useful observations for the calculation of different liquidity measures would no longer suffice to run VAR. To obtain accurate estimations, I only include stocks that have at least 30 valid daily observations to run regressions with one lag and at least 40 valid daily observations to run regressions that contain five lags.

7.3 Lead-Lag Effects in Liquidities

Table 26 summarizes the results of the VAR estimations. In liquidities, I find that eligible and ineligible stocks are mutually influencing as the coefficients and sums of coefficients b and c are significantly different from zero in both one-lag and five-lag regressions. More importantly, all the differences between c and b or ($c - b$) that utilise different illiquidity measurements are both positive and statistically significant at the 1% level. This suggests that eligible stocks have more impact on ineligible stocks' liquidities. Besides, coefficients a and d suggest that liquidities of eligible and ineligible stocks are autocorrelated and self-reinforcing. The results support the hypothesis that eligible stocks would lead the liquidities of ineligible stocks.

I proceed to examine whether these lead-lag effects in liquidities between eligible and ineligible stocks still exist under different market conditions. In **Table 27**, I separate the whole sample period into three cases: days with relatively good market conditions, days with normal market conditions, and days with relatively poor market conditions according to the index return. If the index return is higher (less) than its 80^{th} (20^{th}) percentile, the market condition is defined to be under good (poor)

Table 26. Coefficients from VAR: Lead-lag in Liquidities

Regression using One Lag

	a	b	c	d	Difference ($c-b$)	Observation
Relative Effective Spread	0.157***	0.0145***	0.0224***	0.172***	0.00775***	364,603
	(0.000268)	(0.000129)	(0.000204)	(0.000244)	(0.000227)	
Amihud's Illiquid Ratio	0.0905***	0.0247***	0.0640***	0.0888***	0.0392***	364,603
	(0.000156)	(0.000157)	(0.000491)	(0.000157)	(0.000512)	

Regression using Five Lags

	$\sum_{k=1}^{5} a_k$	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	$\sum_{k=1}^{5} d_k$	Difference ($c-b$)	Observation
Relative Effective Spread	0.226***	0.0270***	0.0412***	0.251***	0.0139***	362,352
	(0.000365)	(0.000261)	(0.000414)	(0.000349)	(0.000472)	
Amihud's Illiquid Ratio	0.213***	0.0725***	0.181***	0.213***	0.108***	362,352
	(0.000289)	(0.000350)	(0.00108)	(0.000288)	(0.00114)	

conditions and the remaining days are defined as normal conditions. In Panels A and C, I initially find that under all three market conditions, eligible stocks still lead ineligible stocks in liquidities given that the differences ($c-b$) are all significantly positive. Then, I perform the difference in differences test by comparing the differences ($c-b$) under different market conditions. The results from Panels B and D suggest that the difference ($c-b$) under good market conditions is higher than the difference under normal and poor market conditions. The distinctive impacts of different channels on the lead-lag effects in liquidity under different market conditions could cause these outcomes. Under a good market condition, the incorporation of the information diffusion's speed into the price is more likely to be at a faster rate. More specifically, this could be due to the lower levels of information asymmetry when market performance is at optimal levels. At the same time, the uncertainty that investor have through asset learning should be lower under good market conditions, since reference stocks tend to have higher liquidity and lower volatility. As a result, the investor has lower levels of uncertainty and the lead-lag effect in liquidity would be stronger. On the other hand, the impact of deleveraging seems to be stronger under poor market conditions, where the funding liquidity tends to be lower than in normal or good market conditions. When the market performs well, the investors are less likely to force liquidate their stocks or face a margin call. In turn, the lead-lag effect will be weaker under good market conditions. It seems that the impacts from information diffusion speed channel and cross asset learning channel have greater explanatory power under good market conditions. Overall, the lead-lag effect in liquidity persists under different market conditions and is stronger when the market is performing well.

I argue that deleveraging's impact on the lead-lag in liquidity is weaker under good market conditions. To further confirm the impact of deleveraging, I choose days with good and poor funding liquidities. Then, I test whether the lead-lag effects still exist and are stronger when the funding liquidity is poor. Theoretically, according to Brunnermeier and Pedersen's (2009) model, investors' funding liquidity or the ease for them to obtain capital is positively related to stocks' liquidities. Also, the stock's market liquidity also depends on the funding liquidity of traders. Furthermore, I use one week's interest rates from the Shanghai Interbank Offered Rate (SHIBOR) as a measurement of funding liquidity. Then, I choose days with stronger funding liquidity constrains where interest rates are higher than the top 20th percentile and days with looser funding liquidity constrains where interest rates are lower than the

Table 27. Coefficients from VAR under different market condition: Lead-lag in Liquidities

Panel A. VAR Coefficients using One-lag Regression

	Good market			Normal			Poor		
	b	c	Difference $(c-b)$	b	c	Difference $(c-b)$	b	c	Difference $(c-b)$
Relative Effective Spread	0.0191***	0.0298***	0.0105***	0.0128***	0.0202***	0.00714***	0.0147***	0.0214***	0.00669***
	(0.000286)	(0.000455)	(0.000507)	(0.000166)	(0.000268)	(0.000296)	(0.000289)	(0.000431)	(0.000488)
Amihud's Illiquid Ratio	0.0247***	0.0710***	0.0462***	0.0235***	0.0581***	0.0346***	0.0284***	0.0745***	0.0460***
	(0.000327)	(0.00115)	(0.00118)	(0.000207)	(0.000626)	(0.000655)	(0.000358)	(0.00108)	(0.00113)

Panel B. Difference in Difference Test using one-lag VAR coefficients

	Normal - Good	Normal - Poor	Good - Poor
Relative Effective Spread	-0.00349***	0.00132*	0.00383***
	(0.000567)	(0.000551)	(0.000704)
Amihud's Illiquid Ratio	-0.00876***	-0.00846***	0.000167
	(0.00131)	(0.00127)	(0.00164)

Panel C. VAR Coefficients using Five-lag Regression

	Good market			Normal			Poor		
	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference $(c-b)$	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference $(c-b)$	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference $(c-\mathrm{b})$
Relative Effective Spread	0.0380***	0.0592***	0.0209***	0.0230***	0.0359***	0.0125***	0.0277***	0.0385***	0.0109***
	(0.000575)	(0.000918)	(0.00104)	(0.000337)	(0.000543)	(0.000617)	(0.000592)	(0.000877)	(0.00102)
Amihud's Illiquid Ratio	0.0709***	0.199***	0.128***	0.0718***	0.172***	0.100***	0.0764***	0.186***	0.110***
	(0.000717)	(0.00251)	(0.00261)	(0.000465)	(0.00139)	(0.00147)	(0.000782)	(0.00234)	(0.00247)

Panel D. Difference in Difference Test using five-lag VAR coefficients

	Normal - Good	Normal - Poor	Good - Poor
Relative Effective Spread	-0.00875***	0.00375**	0.00996***
	(0.00117)	(0.00115)	(0.00146)
Amihud's Illiquid Ratio	-0.0257***	-0.00225	0.0186***
	(0.00290)	(0.00278)	(0.00359)

bottom 20^{th} percentile. Ultimately, I compare the lead-lag relations in liquidity during these two situations. **Table 28** summarizes the results. First, I find that the differences ($c - b$) under both high funding liquidity or low funding liquidity conditions are positive and statistically significant. This implies that regardless of strict or loose funding constraints that the investors face, the lead-lag relations in liquidity still exist. More importantly, the difference in difference test results indicate that the lead-lag effect (measured by the difference between c and b) is weaker when investors have higher funding liquidity. In contrast, when investors face low liquidity in funding with higher interest rates and stricter funding constrains, the lead-lag effect in liquidity is much stronger. This result supports Brunnermeier and Pedersen's (2009) model which links the funding liquidity with stocks' market liquidity. If there is an initial loss in investors' leverage trading positions while the funding liquidity is also at a low level, this could lead to the reduces in position and further result in decrease in stock prices. As a result, in order to maintain the capital required for the margin requirement and avoid force liquidation, investors have to either reduce the leverage level or even sell other un-leveraged stocks. On the other hand, when investors face high funding liquidity, it would be easier for them to gain the capital to maintain the margin requirements without trading leveraged or un-leveraged stocks. Thus, the results support that deleveraging could be a channel that helps explain the lead-lag relations in liquidity.

Table 28. Funding Liquidity and Lead-lag in Liquidity

Panel A: One-lag Regression

	High Funding Liquidity			Low Funding Liquidity		
	b	c	Difference ($c-b$)	b	c	Difference ($c-b$)
Relative Effective Spread	0.0150***	0.0220***	0.00696***	0.0137***	0.0236***	0.00975***
	(0.000283)	(0.000420)	(0.000477)	(0.000274)	(0.000485)	(0.000527)
Amihud's Illiquid Ratio	0.0293***	0.0673***	0.0380***	0.0137***	0.0649***	0.0511***
	(0.000343)	(0.000899)	(0.000957)	(0.000297)	(0.00142)	(0.00144)

Panel B: Difference in Difference Test: High – Low

Relative Effective Spread	-0.00280***
	(0.00071)
Amihud's Illiquid Ratio	-0.0131***
	(0.00173)

Panel C: Five-lag Regression

	High Funding Liquidity			Low Funding Liquidity		
	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference ($c-b$)	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference ($c-b$)
Relative Effective Spread	0.0300***	0.0436***	0.0134***	0.0254***	0.0418***	0.0161***
	(0.000576)	(0.000851)	(0.000989)	(0.000552)	(0.000978)	(0.00109)
Amihud's Illiquid Ratio	0.0826***	0.172***	0.0891***	0.0446***	0.214***	0.170***
	(0.000738)	(0.00191)	(0.00205)	(0.000668)	(0.00320)	(0.00325)

Panel D: Difference in Difference Test: High – Low

Relative Effective Spread	-0.00264
	(0.00147)
Amihud's Illiquid Ratio	-0.0807***
	(0.00385)

7.4 Lead-Lag Effects in Returns

In this chapter, I focus on the lead-lag effects in return. To investigate the process of price discovery, I execute the same VAR estimation using Equations (1) and (2) on the returns. **Table 29** reports all VAR results. The lead-lag effect in returns exists and eligible stocks lead the changes in the prices of ineligible stocks. Moreover, by comparing the coefficients a and d from one-lag regressions and five-lag regressions, I find that returns have mean-reverting patterns in the five-minute interval. While in very short periods, (i.e. one minute), returns tend to be positively

Table 29. Coefficients from VAR: Lead-lag in Returns

Regression using One Lag

	a	b	c	d	Difference ($c-b$)	Observation
Return	-0.000162	0.0679***	0.108***	0.0299***	0.0401***	364,603
	(0.000321)	(0.000156)	(0.000218)	(0.000316)	(0.000254)	

Regression using Five Lags

	$\sum_{k=1}^{5} a_k$	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	$\sum_{k=1}^{5} d_k$	Difference ($c-b$)	Observation
Return	-0.287***	0.142***	0.235***	-0.245***	0.0927***	362,352
	(0.000561)	(0.000368)	(0.000506)	(0.000547)	(0.000600)	

autocorrelated.

Similar to the previous section, I separate the whole sample into three different market conditions. **Table 30** lists the corresponding results. Notably, in all three different market conditions, eligible stocks still lead ineligible stocks in the returns given that the differences between c and b are positive and statistically significant. However, in contrast with the results in liquidity comovements, comovements in returns are strongest under poor market conditions.

As mentioned in the introduction, three channels could explain the formation of lead-lag effects in returns, where one is through deleveraging. When the market is under poor conditions, the investors are more likely to force liquidate their leverage trading and sell ineligible stocks to raise sufficient capital to meet the margin requirement. As a result, the lead-lag in returns will be stronger under poor market conditions. On the contrary, the information diffusion speed would be slower under such market conditions, the liquidity will be lower, and the risk of eligible stocks brought upon by volatility is probably higher. Consequently, this leads to weaker lead-lag relations in the returns. However, in spite of the discrepancies on the impacts across these three channels, I use the mediation analysis to prove (Section 7.6 Figure 3) that the deleveraging channel accounts for 70.73% of the total impact of leveraged trading on lead-lag in returns. Consequently, the deleverage channel dominates the total effect, making lead-lag effects the strongest under poor market conditions.

Table 30. Coefficients from VAR under Different Market Conditions: Lead-lag in Returns

Lag 1									
	Good market			**Normal**			**Poor**		
	b	c	Difference ($c-b$)	b	c	Difference ($c-b$)	b	c	Difference ($c-b$)
Return	0.0643*** (0.000347)	0.105*** (0.000486)	0.0403*** (0.000573)	0.0582*** (0.000187)	0.0905*** (0.000261)	0.0323*** (0.000307)	0.101*** (0.000390)	0.164*** (0.000526)	0.0631*** (0.000650)
Difference in Difference Test									
	Normal - Good			**Normal - Poor**			**Good - Poor**		
Relative Effective Spread	-0.000282 (0.000639)			-0.0287*** (0.00070)			-0.0228*** (0.000867)		
Lag 5									
	Good market			**Normal**			**Poor**		
	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference ($c-b$)	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference ($c-b$)	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference ($c-b$)
Return	0.124*** (0.000788)	0.209*** (0.00110)	0.0853*** (0.00128)	0.133*** (0.000464)	0.213*** (0.000636)	0.0803*** (0.000757)	0.189*** (0.000892)	0.328*** (0.00119)	0.138*** (0.00148)
Difference in Difference Test									
	Normal - Good			**Normal - Poor**			**Good - Poor**		
Relative Effective Spread	0.00929*** (0.00145)			-0.0566*** (0.00162)			-0.0528*** (0.00196)		

7.5 Robustness Check

7.5.1 Portfolio Analysis

The literature argues that using only three criteria in matching could miss some firm-specific characteristics and cause the matching to be less accurate. To solve this problem, I construct two portfolios where one contains all eligible stocks and the other with all the ineligible stocks in the market. Then, I compute the average liquidities and returns for each portfolio and run the VAR following equations (9) and (10). **Table 31** summarizes the results of this portfolio analysis.

Table 31. Coefficients from VAR: Portfolio Analysis

Regression using One Lag

	a	b	c	d	Difference ($c-b$)	Observation
Relative Effective Spread	0.517***	0.158***	0.249***	0.673***	0.0904***	540
	(0.00596)	(0.00334)	(0.00742)	(0.00436)	(0.00921)	
Amihud's Illiquid Ratio	0.289***	0.00596***	1.120**	0.150***	1.114**	540
	(0.00931)	(0.000440)	(0.493)	(0.00750)	(0.493)	
Return	0.711***	-0.0158***	0.792***	0.980***	0.808***	540
	(0.00310)	(0.000514)	(0.00574)	(0.000657)	(0.00583)	

Regression using Five Lags

	$\sum_{k=1}^{5} a_k$	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	$\sum_{k=1}^{5} d_k$	Difference ($c-b$)	Observation
Relative Effective Spread	0.629***	0.134***	0.213***	0.757***	0.0785***	540
	(0.00645)	(0.00408)	(0.00868)	(0.00578)	(0.0109)	
Amihud's Illiquid Ratio	0.489***	0.0120***	2.972***	0.309***	2.960***	540
	(0.0122)	(0.000778)	(0.699)	(0.0105)	(0.699)	
Return	0.665***	-0.00802***	1.911***	0.989***	1.919***	540
	(0.00954)	(0.000323)	(0.0262)	(0.000485)	(0.0262)	

The eligible stocks still lead ineligible stocks in both liquidities and returns since differences (c – b) in both regressions and both liquidity measures are positive and statistically significant. Interestingly, the coefficients *b* for returns are negative in both regressions. This suggests that a decrease in the past minute return of ineligible stocks would actually improve the overall return of eligible stocks.

7.5.2 Firm Size

The previous VAR results demonstrate that stocks eligible for margin-trading and short-selling lead the changes in liquidity and returns of stocks that are ineligible. It is possible that firm-level characteristics like a firm's size cause these lead-lag relationships in liquidities and returns (Lo and MacKinlay, 1990; Hou and Moskowitz, 2005; Hou, 2007). For example, Hou and Moskowitz (2005) use price delay in weekly returns and propose that firm size and lead-lag effects in the weekly returns are partially correlated. They believe that the industry information diffuses at a slower rate in small-sized firms to the extent that their prices change at a slower rate than large-sized firms.

Table 32. Coefficients from VAR: Firm size

	One-Lag Regression		**Five-Lag Regression**	
	Effective Spread	Amihud's Illiquid	Effective Spread	Amihud's Illiquid
b	0.01614***	0.03306***	0.03099***	0.09693***
	(0.00033)	(0.00043)	(0.00068)	(0.00096)
c	0.01907***	0.03753***	0.03548***	0.1053***
	(0.00041)	(0.00064)	(0.00082)	(0.00139)
Difference	0.002994***	0.004473***	0.004431***	0.008363***
($c-b$)	(0.00049)	(0.00076)	(0.00103)	(0.00169)
Observation	66,701	66,701	66,331	66,331

To prove that the nature of eligible stocks with higher market capitalization is not the sole cause of the lead-lag effect in this chapter, I choose the matching pairs where ineligible stocks have larger firm sizes than eligible stocks. Then, I compare the coefficients c and d to test for the existence of the lead-lag effects. Evidently, for those non-margin stocks with higher firm sizes than margin stocks, the lead-lag effects in liquidity and returns still exist.

7.5.3 Event Study Analysis

I execute the following event studies to prove that the lead-lag effects in liquidities and return become stronger when bans on margin trading and short selling are lifted. Additionally, this study substantiates that not only firm characteristics of eligible stocks (large firm sizes and high trading volumes) but also their role in leverage trading, cause the lead-lag effects in liquidities and returns between eligible and ineligible stocks.

On September 22, 2014, the number of stocks eligible for margin-trading and short-selling increased from 700 to 900. So, I only select the 200 newly added eligible stocks and compare their lead-lag in liquidities and returns before and after the inception date. In spite of those 200 stocks ineligible for margin-trading and short-selling before the inception date, I still find them leading other ineligible stocks in liquidity and returns given that they are large in firm size and trading volume. Then, I compare the differences ($c - b$) between before and after the event date. I find that lead-lag relations in both liquidities and returns increased after these stocks became eligible for margin-trading and short-selling. This result suggests that become eligible for margin-trading and short-selling contributes to the increase in lead-lag effects.

Table 33. Event Study: Coefficients from VAR Before and After 5th Inception Date

One-lag Regression

	180 days Before			180 days After		
	b	c	Difference ($c-b$)	b	c	Difference ($c-b$)
Relative Effective	0.0155***	0.0218***	0.00613***	0.0166***	0.0242***	0.00755***
Spread	(0.000443)	(0.000657)	(0.000741)	(0.000436)	(0.000675)	(0.000756)
Amihud's Illiquid	0.00779***	0.0249***	0.0169***	0.0143***	0.0360***	0.0216***
Ratio	(0.000552)	(0.00151)	(0.00159)	(0.000484)	(0.00135)	(0.00141)
Return	0.0256***	0.0321***	0.00655***	0.0420***	0.0555***	0.0135***
	(0.000422)	(0.000488)	(0.000643)	(0.000474)	(0.000599)	(0.000740)

Difference in Difference Test: Before – After

Relative Effective	-0.00141***
Spread	(0.0000821)
Amihud's Illiquid	-.00469***
Ratio	(.000165)
Return	-.00695***
	(.0000868)

Five-lag Regression

	180 days Before			180 days After		
	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference ($c-b$)	$\sum_{k=1}^{5} b_k$	$\sum_{k=1}^{5} c_k$	Difference ($c-b$)
Relative Effective	0.0304***	0.0445***	0.00847***	0.0339***	0.0536***	0.00869***
Spread	(0.00364)	(0.00663)	(0.00173)	(0.00188)	(0.00540)	(0.00166)
Amihud's Illiquid	0.0440***	0.134***	0.0613***	0.0493***	0.119***	0.0665***
Ratio	(0.00280)	(0.00924)	(0.00483)	(0.00281)	(0.00424)	(0.00346)
Return	0.103***	0.125***	0.0219***	0.0956***	0.132***	0.0359***
	(0.00122)	(0.00140)	(0.00179)	(0.00115)	(0.00144)	(0.00176)

Difference in Difference Test: Before – After

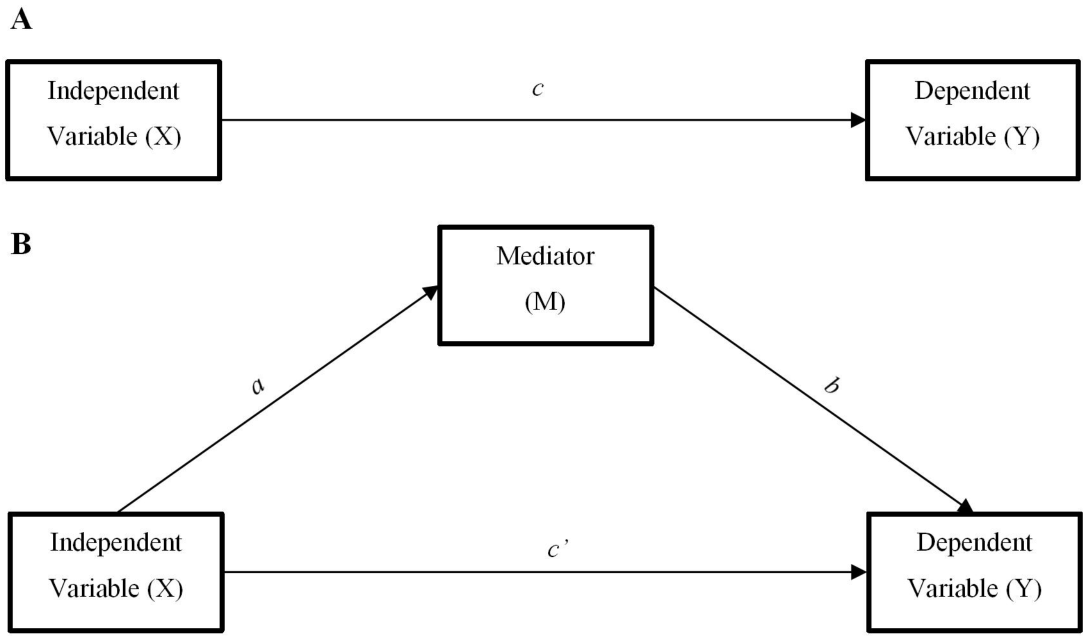
Relative	-0.000220
Effective Spread	(0.000188)
Amihud's	-0.00569***
Illiquid Ratio	(0.000465)
Return	-0.0140***
	(0.000216)

7.6 Mechanism Analysis

The previous sections highlight how eligible stocks lead ineligible stocks in liquidities and returns. In this section, I will investigate the reasons which cause the lead-lag relationship. Recently, Chen et al. (2016) discovered that margin-trading and short-selling help the price discovery process. Several studies in the literature also suggest that short-selling could enable price discovery while imposing bans on short-selling would decrease liquidities. Therefore, I assume that margin-trading and/or short-selling will influence the lead-lag effects in liquidities and returns. As mentioned in the introduction, three channels could help explain the impact of leverage trading on lead-lag effects in liquidity and return, namely the information diffusion speed, cross-asset learning, and deleveraging. To understand how each channel affects the lead-lag effect, I estimate several mediation models and compare the magnitude and significance of these channels.

Many researchers in behavioral science apply the mediation analysis to investigate causal effects. As illustrated in Figure 4 (A), the independent variable X directly affects dependent variable Y with a total effect of c. X and Y are believed to be the cause and effect. However, X may influence Y through another variable, known as a mediator. Figure 4 (B) illustrates a simple case of the mediation effect, which only contains one mediator M. In this case, independent variable X's casual effect on dependent variable Y could be classified as an indirect effect through the mediator M (path ab) and direct effect (path c'). More specifically, path a represents the impact of X on the proposed mediator M and path b represents the effect of M on dependent variable Y while excluding the effect of X. Additionally, the relation of direct effect and indirect effect is $c = c' + a \times b$ (Preacher and Hayes, 2004, 2008).

Figure 4. Direct Effect and Mediation Effect (Adapted from Preacher and Hayes, 2008)



To perform the mediation analysis, I first define the dependent variable, independent variable, and possible mediators. The dependent variable is the lead-lag effect in liquidity, measured by the difference between coefficients *c* and *b* (i.e. $c - b$) from the VAR analysis. The independent variables are the relative finance interest and relative short interest, as defined in Section 4.2, which are used to measure leveraged trading. Then, I determine the mediators for the analysis. The example above illustrates the simplest case that only includes one mediator. In this chapter, I propose several mediators, which all proved to have indirect impacts on the dependent variable.

To determine the mediators, I refer to the channels that help to explain the impact of leverage trading on lead-lag in liquidity. One of the channels is the speed of information diffusion. According to several research papers (e.g. Hou and

Moskowitz, 2005; Hou, 2007), the prices of large stocks react faster to the industry or market-wide information than small-sized stocks. Since stocks that have large firm sizes are more likely to be eligible for margin-trading and short-selling, as well as leverage trading, I propose to utilize information diffusion speed as a mediator in my mediation analysis. To capture the speed of information diffusion and its incorporation into stock prices, I use the delay in price that follows the work of Hou and Moskowitz (2005). Using the estimates from these two regression equations, I obtain the R^2 that is necessary for calculating the price delay.

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t}$$

$$r_{i,t} = \alpha_i + \sum_{j=0}^{9} \beta_{i,j} r_{m,t-j} + \varepsilon_{i,t}^{r}$$

where $r_{i,t}$ is the stock return at time t and $r_{m,t}$ is the market return at time t. After running these two regressions, the R^2 from both regressions are recorded as $R_{i,\tau}^{2,\,Restricted}$ and $R_{i,\tau}^{2,\,Unrestricted}$ respectively. When market-wide information is not immediately reflected in the individual stock's return, the R^2 from the first regression would be less than the second regression. The price delay is then calculated as:

$$\text{Price Delay}_{i,\tau} = 1 - \frac{R_{i,\tau}^{2,\,Restricted}}{R_{i,\tau}^{2,\,Unrestricted}}$$

When the information is held in prices, which leads to a price delay, the $R_{i,\tau}^{2,\,Unrestricted}$ will be higher than $R_{i,\tau}^{2,\,Restricted}$.

The second channel known as cross asset learning takes place when investors hold one stock will use the price of another as a benchmark. As Cespa and Foucault (2014) argue, a decrease in the liquidity of one stock leads to a decrease in another. Therefore, I propose liquidity as one of the mediators while using the liquidity of eligible stock as a form of measurement. The relative effective spread of eligible stocks is used as the mediator.

I also assume that investors will acquire price informativeness through a stock's volatility that measures uncertainty in the stock's price from the investors' perspective. Additionally, I propose volatility as another mediator in this mediation analysis. To measure volatility, I use the intraday high-frequency data.

$$\text{Intraday Volatility}_i = \sqrt{Var(r_{i,t})}$$

where $r_{i,t}$ is the stock's return at time *t*. So, for each stock *i*, the volatility is recalculated daily.

The mediators of my analysis are price delay that measures the information diffusion speed, relative effective spread that measures liquidity from cross asset learning, and intraday volatility that measures a stock's volatility from the cross asset learning channel. After considering the effects through these mediators, the remaining impact is the direct effect that takes place through deleveraging.

If a mediated effect exists, the estimations from regressions that include mediators should satisfy the following three conditions. First, the independent variable affects the dependent variable when running a regression of the dependent variable on the independent variable. In my case, I test how leverage trading impacts lead-lag effects in liquidity in Model (1) using the following specification:

$$\text{Lead-lag in Liquidity}_{i,t} = \alpha_{i,t} + \beta \text{relative finance interest}_{i,t} + \theta \text{relative short interest}_{i,t} + \boldsymbol{\gamma X_{i,t}} + \varepsilon_{i,t} \qquad \text{Model (1)}$$

Second, the independent variable should affect the mediators when running the regression of the mediators on the independent variable. I test them in models (2), (3), and (4). While testing the independent variable's impact on the mediators, I also include other mediators in each regression since mediators could influence one another. Model (2) tests how leverage trading influences price delay. Additionally, I consider the relationships between price delay, liquidity, and intra-day volatility since both liquidity and volatility could contribute to the information diffusion speed.

$$\text{Price Delay}_{i,t} = \alpha_{i,t} + \beta_1 \text{relative finance interest}_{i,t} + \theta_1 \text{relative short interest}_{i,t} + \mu_1 \text{Illiquidity}_{i,t} + \mu_2 \text{Intraday Volatility}_{i,t} + \boldsymbol{\gamma X_{i,t}} + \varepsilon_{i,t} \qquad \text{Model (2)}$$

Model (3) tests how leverage trading affects liquidity while considering the impact of the other two mediators known as price delay and volatility.

$$\text{Illiquidity}_{i,t} = \alpha_{i,t} + \beta_2 \text{relative finance interest}_{i,t} + \theta_2 \text{relative short interest}_{i,t} + \mu_3 \text{Price Delay}_{i,t} + \mu_4 \text{Intraday Volatility}_{i,t} + \boldsymbol{\gamma X_{i,t}} + \varepsilon_{i,t} \qquad \text{Model (3)}$$

Model (4) tests how leverage trading influences intraday volatility.

$$\text{Intraday Volatility}_{i,t} = \alpha_{i,t} + \beta_3 \text{relative finance interest}_{i,t} + \theta_3 \text{relative short interest}_{i,t} + \mu_5 \text{Price Delay}_{i,t} + \mu_6 \text{Illiquidity}_{i,t} + \boldsymbol{\gamma X_{i,t}} + \varepsilon_{i,t} \qquad \text{Model (4)}$$

The final condition is the mediator and independent variable affect the dependent variable in a regression of the dependent variable on both the independent and mediator variables, which I test in Model (5). In addition, the estimates of independent variables in Model (5) should be less than the estimates of the independent variable from Model (1) to have a mediation effect. Model (5) measures the direct effect of leverage trading on comovement in liquidity, while also measuring the indirect effect of liquidity, price delay, and volatility on lead-lag in liquidity.

$$\text{Lead-lag in Liquidity}_{i,t} = \alpha_{i,t} + \beta_0 \text{relative finance interest}_{i,t} + \theta_0 \text{relative short interest}_{i,t} ++ \beta_4 \text{Price Delay}_{i,t} + \beta_5 \text{Illiquidity}_{i,t} + \beta_6 \text{Volatility}_{i,t} + \boldsymbol{\gamma X_{i,t}} + \varepsilon_{i,t} \qquad \text{Model (5)}$$

All panel regressions are controlled for both firm fixed effect and time fixed effect. Estimates from Models (1) to (5) are listed in **Table 34**. The results suggest that relative finance interest, as an independent variable, satisfy all three conditions

Table 34: Lead-lag in Liquidity and Mediators Regressions

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	Lead-lag in Liquidity	Price Delay	Relative Effective Spread	Intraday Volatility	Lead-lag in Liquidity
Relative Finance Interest	0.0602***	-0.485***	-0.0847**	-0.344***	0.0350**
	(0.0170)	(0.0892)	(0.0406)	(0.0283)	(0.0177)
Relative Short Interest	1.745	-37.68*	-7.580*	22.60***	2.504
	(3.994)	(19.82)	(4.411)	(4.387)	(3.978)
Price Delay			0.0231***	0.0220***	-0.00202*
			(0.00271)	(0.00131)	(0.00116)
Relative Effective Spread		0.365***		0.282***	-0.0211***
		(0.0404)		(0.0122)	(0.00599)
Intra-day Volatility		0.309***	0.250***		-0.0465***
		(0.107)	(0.0843)		(0.0146)
Price	0.0235***	0.393***	-0.0178	0.0896***	0.0296***
	(0.00644)	(0.0320)	(0.0142)	(0.0107)	(0.00639)
Firm Size	-0.0187	-0.536*	-0.405***	-0.905***	-0.0884
	(0.0552)	(0.281)	(0.130)	(0.174)	(0.0592)
Trading Volume	-0.808	18.27**	-21.62***	54.31***	1.555
	(0.815)	(7.465)	(4.582)	(2.757)	(1.154)
Volatility	-0.201***	-2.110***	-0.358*	2.247***	-0.0939**
	(0.0339)	(0.304)	(0.197)	(0.0650)	(0.0472)
Ownership Concentration	-0.00589	0.0706**	0.0121**	-0.00913	-0.00565
	(0.00492)	(0.0290)	(0.00575)	(0.00624)	(0.00489)
Return	0.0166	0.0388	-0.0712***	0.300***	0.0315***
	(0.0105)	(0.0603)	(0.0266)	(0.0321)	(0.0113)
HS300	-0.000866	-0.0208**	-0.00218	0.0155***	-0.000135
	(0.00185)	(0.00937)	(0.00253)	(0.00255)	(0.00185)
Price Limit	-0.00288*	0.0297***	0.00863***	0.00148	-0.00235
	(0.00166)	(0.00723)	(0.00211)	(0.00404)	(0.00170)
Constant	0.00932***	0.257***	0.117***	0.0926***	0.0202***
	(0.00342)	(0.0217)	(0.0123)	(0.00633)	(0.00380)
Observations	362,980	362,636	362,636	362,636	362,636
R-squared	0.010	0.370	0.469	0.731	0.010

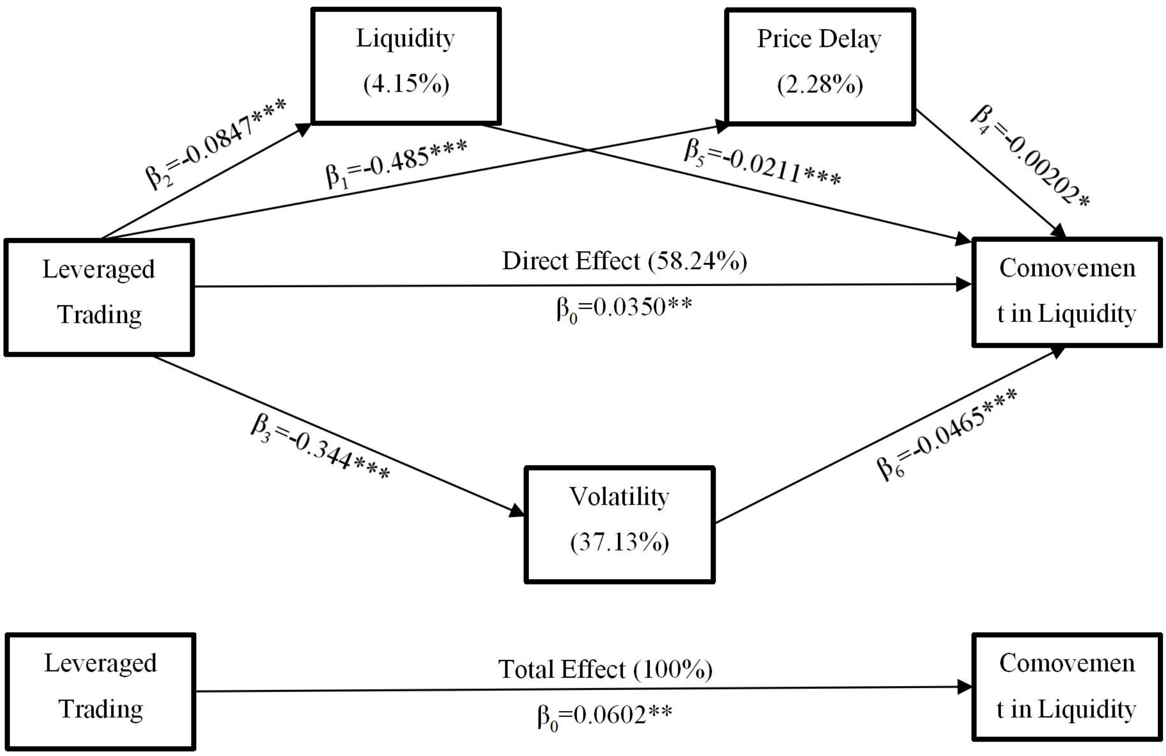
In column (1) and column (5) the dependent variable is lead-lag in liquidity. In column (2), the dependent variable is price delay; in column (3), the dependent variable is the relative effective spread and in column (4), the dependent variable is intraday volatility. For all regressions in this table, independent variables are relative finance interest and relative short interest. Price, Firm size, Volume, Turnover, Volatility and Ownership Concentration are used as control variables. All regressions are controlled for the time fixed effect as for every day, one daily dummy variable is included in the regression and for each firm, the fixed effect is also used. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

while relative short interest does not because of its insignificant impact on the dependent variable in models (1) and (5). Moreover, the coefficient on relative finance interest from Model (5) is less than the one derived from Model (1), suggesting that there could be a mediation effect. Apart from this, the independent variable affects each mediator variable that explains the dependent variable, implying that they could be regarded as mediators. Model (1) highlights that margin-trading directly influences the lead-lag in liquidity. Higher positions in margin-trading will lead to stronger lead-lag effects. Additionally, relative finance interest is negatively associated with the price delay, suggesting that higher levels of leverage will improve the speed of information diffusion. Results from Models (3) and (4) suggest that margin-trading negatively affects the measure of illiquidity, which is consistent with the previous chapter's findings. Also, margin-trading reduces a stock's volatility. Estimates from Model (5) suggest that margin-trading still influences the lead-lag in liquidity, even after including the impacts from the mediators. Moreover, these mediators are all negatively and statistically significant related to the lead-lag effects in liquidity, suggesting that all three channels could help explain leverage trading's impact on lead-lag in liquidity.

In the previous analysis, I proved that margin-trading contributes to the lead-lag effects in liquidity. In this case, all mediators contribute to explaining the lead-lag effects in liquidity. Then, I calculate the proportion of each channel. In line with Preacher and Hayes (2004, 2008), I first compare the total effect β with the direct effect β_0 and calculate that the direct effect that accounts for 58.24% (=$\beta_0 \div \beta$) of the total effect. Then, the indirect effect accounts for 42.76% (=1–58.24%) of the total effect. As proposed, three channels could help explain the impact of leverage trading on the lead-lag in liquidity. The remaining indirect effect will be divided into these three channels according to the estimators from the regressions. For instance, the corresponding impact of the information diffusion speed channel on the lead-lag effect in liquidity is calculated as $\frac{\beta_1\beta_4}{\beta_1\beta_4+\beta_2\beta_5+\beta_3\beta_6} \times 42.76\% = 2.28\%$. Similarly, the indirect effect through the liquidity channel is 4.15% (=$\frac{\beta_2\beta_5}{\beta_1\beta_4+\beta_2\beta_5+\beta_3\beta_6} \times 42.76\%$) and volatility is equal to 37.13% ($=\frac{\beta_3\beta_6}{\beta_1\beta_4+\beta_2\beta_5+\beta_3\beta_6}\times 42.76\%$). **Figure 5** illustrates the relationships between the independent variable, mediators, and dependent variables.

Certainly, margin-trading would improve the comovements in liquidity through four channels. The first is the direct effect through deleveraging, which accounts for 58.24% of the total effect. An increase in margin-trading position would lead to a stronger lead-lag in liquidities between stocks eligible and ineligible for margin-trading and short-selling. When leveraged trading investors encounter some mispricing in margin stocks, a higher margin position would lead to a higher funding demand and an increased possibility of selling non-margin stocks. The second channel is information diffusion. Only 2% of the impact of margin-trading on comovements in liquidity occurs via faster diffusion in market-wide information. This suggests that leverage trading does reduce price delays and increases the speed at which market-wide information is transmitted from large to small-cap firms' stocks. However, the impact is very subtle. The third channel, cross asset learning, explains 41.28% (=4.15%+37.13%) of the total effect. Leverage trading improves the liquidity and decrease the volatility of eligible stocks. Also, investors that use eligible stocks as their benchmark will have increased informativeness, which decreases the uncertainty in their stocks. Hence, the liquidity of the stocks they hold will also increase.

Figure 5. Direct and Mediated Effect of Leverage Trading on Lead-lag in Liquidity



I also perform the same mediation analysis on lead-lag in returns. **Table 35** highlights the estimations from regressions. Similar to the results from **Table 34** that uses lead-lag in liquidity, I find that only margin-trading position has a positive total effect and direct effect on lead-lag in returns. The proposed mediators also influence the lead-lag in returns. Then, I calculate the corresponding proportions of each channel, which explains the impact of leverage trading on lead-lag in returns. **Figure 6** shows the results.

In addition, **Figure 6** illustrates that the information diffusion speed channel only accounts for 0.86% of the total effect, while the cross asset learning channel is responsible for 28.41% of the total effect. The remaining 70.73% goes to deleveraging, which is the direct effect channel. Since the deleverage channel's

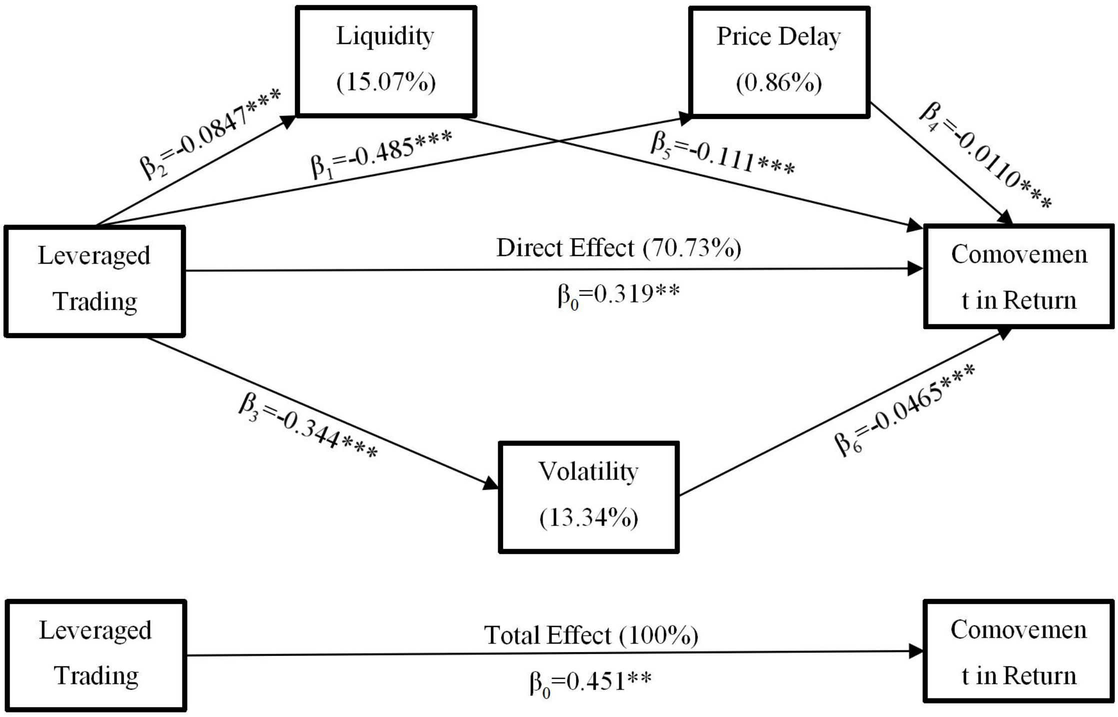
Table 35: Lead-lag in Return and Mediators Regressions

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Lead-Lag in Return	Price Delay	Relative Effective Spread	Intraday Volatility	Lead-Lag in Return
Relative Finance Interest	0.451***	-0.485***	-0.0847**	-0.344***	0.319***
	(0.0403)	(0.0892)	(0.0406)	(0.0283)	(0.0466)
Relative Short Interest	-7.129	-37.68*	-7.580*	22.60***	-2.666
	(6.576)	(19.82)	(4.411)	(4.387)	(6.487)
Price Delay			0.0231***	0.0220***	-0.0110***
			(0.00271)	(0.00131)	(0.00249)
Relative Effective Spread		0.365***		0.282***	-0.111***
		(0.0404)		(0.0122)	(0.0252)
Intra-day Volatility		0.309***	0.250***		-0.242***
		(0.107)	(0.0843)		(0.0871)
Price	-0.0259**	0.393***	-0.0178	0.0896***	0.00618
	(0.0122)	(0.0320)	(0.0142)	(0.0107)	(0.0128)
Firm Size	0.731***	-0.536*	-0.405***	-0.905***	0.365***
	(0.129)	(0.281)	(0.130)	(0.174)	(0.123)
Trading Volume	-2.543	18.27**	-21.62***	54.31***	9.777**
	(2.089)	(7.465)	(4.582)	(2.757)	(4.917)
Volatility	-0.696***	-2.110***	-0.358*	2.247***	-0.143
	(0.0706)	(0.304)	(0.197)	(0.0650)	(0.212)
Ownership Concentration	-0.0100	0.0706**	0.0121**	-0.00913	-0.00861
	(0.00889)	(0.0290)	(0.00575)	(0.00624)	(0.00773)
Return	-0.101***	0.0388	-0.0712***	0.300***	-0.0249
	(0.0265)	(0.0603)	(0.0266)	(0.0321)	(0.0343)
HS300	-0.00863**	-0.0208**	-0.00218	0.0155***	-0.00489
	(0.00336)	(0.00937)	(0.00253)	(0.00255)	(0.00345)
Price Limit	0.00606*	0.0297***	0.00863***	0.00148	0.00890***
	(0.00346)	(0.00723)	(0.00211)	(0.00404)	(0.00337)
Constant	0.0247***	0.257***	0.117***	0.0926***	0.0819***
	(0.00717)	(0.0217)	(0.0123)	(0.00633)	(0.0106)
Observations	362,894	362,636	362,636	362,636	362,550
R-squared	0.093	0.370	0.469	0.731	0.108

In column (1) and column (5) the dependent variable is lead-lag in return. In column (2), the dependent variable is price delay; in column (3), the dependent variable is the relative effective spread and in column (4), the dependent variable is intraday volatility. For all regressions in this table, independent variables are relative finance interest and relative short interest. Price, Firm size, Volume, Turnover, Volatility and Ownership Concentration are used as control variables. All regressions are controlled for the time fixed effect as for every day, one daily dummy variable is included in the regression and for each firm, the fixed effect is also used. The numbers reported in parentheses are standard errors. The estimates with three (***), two(**), one (*) asterisks are statistically significant at 1%, 5%, 10% level.

impact is much stronger when the market is under poor conditions, this result helps to explain the observations from **Table 30** that confirms how the lead-lag relationship under poor market conditions is at its strongest. When the market is under a crisis period, even though the impacts from the information diffusion speed and cross asset learning channels weaken, the impact from deleveraging dominates. Thus, the lead-lag relations are stronger under poor market conditions.

Figure 6. Direct and Mediated Effect of Leverage Trading on Lead-lag in Returns



7.7 Conclusion

Using intraday high-frequency data reveals a strong lead-lag relationship in liquidities and returns between stocks that are eligible and ineligible for margin-trading and short-selling. Moreover, this lead-lag relation holds under different market conditions. When using all eligible stocks in a portfolio and all ineligible stocks in another, the lead-lag effect still exists in both liquidities and returns. The results from the event study further prove that this lead-lag effect exists because of leverage trading. Then, using mediation analysis, I find that relative finance interest help explain the lead-lag effect in liquidities and returns. Additionally, I proposed three mediators to help explain the impact of leverage trading on lead-lag effects. I use price delay to capture the information diffusion channel, as well as the illiquidity measure and intraday volatility to capture the cross asset learning channel. The deleveraging channel is the direct effect that leverage trading has on lead-lag effects. Ultimately, I find that information diffusion only explains a small proportion of the total effect while deleveraging directly explains over half of the total effect.

CHAPTER 8: CONCLUSIONS

8.1 Summary and Implications

In Chapter 5, I prove that common determinants of liquidity in the literature are also determinants in the Chinese stock market. Stock trading activities like price and trading volume are positively related to liquidity while volatility is negatively correlated to liquidity. On the firm specific characteristic level, stocks with larger firm size tend to have lower spreads and price impact measures but stocks with higher ownership concentration seem to have lower liquidity. Moreover, I also prove that whether stocks are index components, whether stocks hit the price limit and the stocks' trading status are also determinants of liquidity.

The evidence in Chapter 6 suggests that stocks eligible for margin-trading and short-selling tend to have higher liquidity than ineligible stocks. The result from event study further proves that lifting bans on margin-trading and short-selling improves liquidity of eligible stocks. This finding is consistent with several literature in which researchers argue that bans on short-selling is harmful to the liquidity (Battali and Schultz, 2011; Marsh and Payne, 2012; Beber and Pagano, 2013; Alves, Mendes and da Silva, 2016). When focusing on margin-trading and short-selling activities using sub-sample that contains only stocks allowed for margin-trading and short-selling, the results suggest that both the position and trading level of margin-trading has a beneficial effect on liquidity. On the contrary, short-selling is proved to be detrimental for liquidities. To explain this negative impact of short-selling on liquidity, I argue that it is caused by the adverse selection. I prove that short-sellers can predict the future return while margin-traders cannot. In addition, I also prove that short-selling has strongest impact among firms with highest information asymmetry level. Then I also focus on the crisis period and investigate whether the impact of eligibility and margin-trading and short-selling will be different. The results suggest that stocks eligible for margin-trading and short-selling actually have lower liquidity when market is under poor condition. Moreover, opposite to their impact under normal market condition, margin-trading hampers the stock's liquidity while short-selling improves the liquidity. All results have practical implications. First, findings that under extreme poor market condition, short-selling actually improves the liquidity is consistent with several studies that focus on the impact of short-sale bans during the financial crisis period (e.g. Marsh and Payne, 2012; Beber and Pagano, 2013; Alves, Mendes and da Silva, 2016). Prohibiting short-sale will not improve the liquidity during the market crash period. However, from the regulators aspect, they believe that short-selling is harmful to the stock's liquidity is also understandable as the result using the whole sample period suggests that short-selling decreases stock's liquidity. Therefore, this study reconciles the discrepancy between some literature and regulators.

In Chapter 7, by using the VAR estimations, I find lead-lag effects between liquidities of eligible and ineligible stocks. Stocks allowed for margin-trading and short-selling lead stocks that have bans on margin-trading and short-selling in both liquidities and return. This lead-lag effect exists in all different market conditions, even in both extreme market situations. Further robustness tests including event study also justify that the lead-lag relations in liquidity and return between eligible and ineligible stocks. Moreover, the lead-lag relation in liquidity could empirically support the "liquidity spirals" model proposed by Brunnermeier and Pedersen (2009) which predicts that margin requirements destabilize the market in funding constrains periods where stocks' liquidities and funding liquidity would be mutually reinforcing. When the funding liquidity is constrained, the lead-lag effect in liquidity is stronger than that when funding is adequate. Apart from this "deleverage" channel that help explain the impact of leverage trading on the lead-lag relationship in liquidity and return, "information diffusion speed" and "cross asset learning" also explain the impact.

8.2 Limitations and Future Research

One limitation of my thesis is the span of sample period. I end the sample period at the end of 2016. In the future, longer time span could be added into the sample period and more stocks can be included.

Another limitation derives from the special trading rules of the Chinese stock market. When investigating the lead-lag effect in liquidity and return using high-frequency data, it is hard to obtain estimates from VAR during the market crash period as many stocks hit the price limit very soon after the opening leaving insufficient number of observations to do any meaningful statistical analysis. As explained in Chapter 5, when a stock hit the price limit, its liquidity will suddenly dry up as lacking of buying/ selling orders. Thus, it is impossible to focus on the crisis period using minute observations. For future research, comovement at daily level could be investigated.

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