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The impact of short-selling and margin-buying on liquidity: Evidence from the Chinese stock market ☆

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ABSTRACT

We propose a framework based on limit order book to analyze the impact of short-selling and margin-buying on liquidity. We show that when short-sellers are perceived as informed, adverse selection may lead to uninformed traders withdrawing their limit orders. Given that the Chinese stock market has strong information asymmetry and a high proportion of uninformed traders, we predict that the pilot program launched in March 2010, which lifts restrictions on short-selling and margin-buying for a designated list of stocks, may have a negative impact on liquidity. We perform difference-in-differences tests and show evidence that allowing for short-selling and margin-buying indeed has a significantly negative impact on liquidity for stocks on the designated list. In particular, the negative impact on liquidity is more pronounced for stocks with high information asymmetry. Nevertheless, when short-selling volume dries up due to regulation changes in August 2015, i.e., the "T+1" trading rule on short-selling, we show that consistent with model predictions, lifting restrictions on short-selling and margin-buying has a positive effect on liquidity.

1. Introduction

In March 2010, the China Securities Regulatory Commission (CSRC) launched a pilot program to lift restrictions on short-selling and margin-buying for a designated list of 90 stocks. Prior to the pilot program, both short-selling and margin-buying were strictly prohibited in China. The list of designated stocks was expanded and revised subsequently and covered 950 stocks from different industries by December 2016. This event presents a nice setting to examine the effect of short-selling and margin-buying on stock valuation and stock price efficiency, etc. A number of studies have performed empirical analysis and show that lifting restrictions on short-selling and margin-buying in China improves price efficiency (e.g., Chang et al., 2014; Li et al., 2018). Nevertheless, there are relatively fewer studies examining the effect of short-selling and margin-buying on liquidity in the Chinese stock market.

Liquidity is what markets are all about (Amihud and Mendelson, 1988). Over the past decades, the Chinese stock market has displayed extreme levels of volatility, which is partly exacerbated by lack of liquidity. In this regard, liquidity is particularly important for the effectiveness of the Chinese stock market. Therefore, it is necessary to examine the impact of regulatory changes such as the pilot program of short-selling and margin-buying on liquidity in the Chinese stock market.

There is a general consensus that restrictions on short-selling and/or margin-buying have an adverse effect on stock price efficiency. For example, Diamond and Verrecchia (1987) argue that the constraint on short-selling hinders price discovery. Bris et al. (2007) find that prices incorporate negative information more efficiently in countries where short-selling is allowed. Saffi and

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Sigurdsson (2011) find lower efficiency for stocks with more binding short-sale constraints. Chang et al. (2014) show that price efficiency increases after the ban on short-selling and margin-buying is lifted in the Chinese stock market.

However, the literature is less conclusive regarding the effect of short-selling on liquidity. Some studies show that short-sale constraint is associated with deteriorated liquidity. Marsh and Payne (2012) show that the detrimental effects on liquidity persist throughout the relatively long-lasting UK ban on short-selling, but largely disappear once it is lifted. Beber and Pagano (2013) find that the short-selling restrictions during 2007–2009 are detrimental to liquidity globally. Boehmer et al. (2013) provide evidence that stocks subject to the 2008 shorting ban experience declines in liquidity compared to control stocks. Other studies document opposite findings. For instance, Chuang and Lee (2010) show that stocks' liquidity significantly decreases after the short-sale constraints are removed from the component stocks of the Taiwan 50 Index. Jones (2012) finds that the two restrictions on short-sale in the U.S. are associated with improvements in liquidity.[1] Bai and Qin (2014) document that stocks (except large, illiquid and inactively traded stocks) experience a significant drop in liquidity following the repealing of short-sale constraints in the Hong Kong stock market. Different from short-selling, margin-buying is generally acknowledged to improve liquidity in the literature. Seguin (1990) shows that lower margin levels are associated with larger trading volume. Hardouvelis and Peristiani (1992) find that an increase in margin requirements leads to a decline in margin borrowing and trading volume. Kahraman and Tookes (2017) provide evidence that liquidity increases when stocks become eligible for margin-buying and decreases with ineligibility.

In this paper, we present a simple framework based on limit order book (LOB) to analyze the effect of short-selling and margin-buying on liquidity and derive testable implications. There are several advantages of using LOB to examine the effect of short-selling and margin-buying on liquidity. First, LOB is the trading platform for the Chinese stock market and many other financial markets around the world. Second, LOB allows us to define clearly liquidity provision or consumption. Specifically, limit orders placed by short-sellers and margin-buyers supply liquidity, whereas market orders consume liquidity. Lastly, LOB also helps to examine the price impact, which is not only an important dimension of liquidity but also the measure used in our empirical analysis. We show that in a static framework, allowing for short-selling (margin-buying) has a positive effect on the depth of sell (buy) limit orders but a negative effect on the depth at the best bid (ask). The net effect is determined by the limit orders versus market orders submitted by short-sellers and margin-buyers. In a dynamic framework, since orders submitted by short-sellers are perceived as informed (see, Asquith et al., 2005; Boehmer and Wu, 2013; Chang et al., 2014; Diether et al., 2009), uninformed traders may withdraw their limit orders as they are reluctant to trade against informed traders and also avoid the risk of being picked off.[2] As a result, the adverse selection may lead to deteriorated liquidity. Given that the Chinese stock market is characterized as having strong information asymmetry and a high proportion of uninformed traders,[3] we predict that allowing for short-selling and margin-buying may have a negative impact on liquidity for stocks on the designated list. Since adverse selection by uninformed traders is likely to be more pronounced for stocks with high information asymmetry, we further predict that the negative effect is stronger for these stocks.

The pilot program in the Chinese stock market presents an ideal setting to empirically examine our theoretical predictions. Our sample covers 1034 stocks added to the short-selling and margin-buying list from March 2010 to December 2016. We investigate the liquidity change before and after the lift of restrictions on short-selling and margin-buying by comparing treated stocks on the designated list to a matched control group of stocks not on the designated list. Following Beber and Pagano (2013) and Boehmer et al. (2013), we match each treated stock with an untreated stock that is traded in the same exchange and is closest in terms of market capitalization, turnover, and volatility. We use the Amihud (2002) illiquidity ratio in our empirical analysis.

Consistent with our theoretical prediction, we find a significantly negative effect of short-selling and margin-buying on liquidity in the Chinese stock market. The difference-in-differences tests show that relative to untreated control stocks, the treated stocks have significantly higher Amihud (2002) illiquidity ratio after being added to the designated list. The result is robust to further controlling for market capitalization, using alternative event windows, and applying different matching method to construct the control group. However, since there is a general improvement in liquidity in the Chinese stock market over our sample period, one potential concern is that our finding may be driven by the fact that stocks in the control group, which are less liquid, have more potential in liquidity improvement relative to stocks in the treated group. To address this concern, we examine the trends in liquidity for both the treated and control groups and show that differences in liquidity trends between treated and control groups are statistically insignificant during both the pre- and post-event periods as well as the period prior to the pre-event window. We also perform placebo test to rule out other potential confounding effects.

In addition, we examine whether the negative effect of short-selling and margin-buying on liquidity is stronger for stocks with high information asymmetry. Using analysts' earnings forecast dispersion and idiosyncratic volatility as proxies for information asymmetry, the results show that the negative effect on liquidity is indeed stronger for treated stocks with high information asymmetry.

Moreover, we examine one unique feature in the Chinese stock market, i.e., the "T+1" trading rule. The "T+1" trading rule prevents investors from selling stocks bought on the same day. Initially only margin-buying is subject to the "T+1" trading rule. However, during the market crash in June 2015, short-sellers in the Chinese stock market became easy scapegoats. The CSRC began to crackdown on "malicious short sellers" in July 2015 and the regulators imposed a series of restrictions on short-selling as the

[1] The downtick shorting prohibition of October 1931 and the tighter uptick rule of February 1938.

[2] The picking-off risk is that limit sell (buy) orders are susceptible to being picked off or traded at too low (high) a price if the asset value changes (Hollifield et al., 2006; Yamamoto, 2014).

[3] The information asymmetry in China is very likely to be high due to poor corporate governance and low analyst coverage Jiang et al. (2014), widespread share manipulation and insider trading Chan et al. (2008), as well as weak investor protection and monitoring of auditors (Brockman and Chung, 2003; Wang et al., 2008). The Chinese stock market is dominated by individual investors who trade for non-informational reasons (Hirose et al., 2009) and exhibit typical behavior biases, such as herding (Tan et al., 2008) and preference for lottery-like stocks (Wan, 2018).

crash worsened.[4] One of the restrictions is to impose the "T+1" trading rule on short-sellers starting on August 3, 2015.[5] The result of these regulatory changes is that many security brokerages drastically reduced their short-selling business and short-selling activity decreased substantially. The average daily short volume decreased from about 1830 million shares over the 120-day period before August 3, 2015 to about 33 million shares over the 120-day period after. As a result, the adverse selection effect of short-selling is significantly weakened and its negative effect on liquidity may be dominated by the positive effect of margin-buying on liquidity. We perform empirical analysis separately on the first five batches of stocks added to the designated list, which occurred prior to the regulation changes, and the 6th batch of stocks added to the list, which occurred after the regulation changes. The results show that lifting restrictions on short-selling and margin-buying has a negative on liquidity for the first five batches of stocks, but a positive effect for the 6th batch of stocks, consistent with our model predictions.

Our study makes several contributions to the literature. First, we present a simple framework based on limit order book to analyze the effect of short-selling and margin-buying on liquidity. Under the framework, we present testable implications regarding the effect of short-selling and margin-buying on liquidity. Second, our study extends existing studies, such as Sharif et al. (2014) which is based on a sample of 90 stocks of the pilot scheme in 2010. Our empirical analysis is performed over an extended sample period from 2010 to 2016, which not only enhances the power of our analysis but also allows us to examine certain unique features in the Chinese stock market, such as the "T+1" trading rule imposed on short-selling in 2015.

The rest of the paper is structured as follows. Section 2 presents the framework under the limit order book and our theoretical predictions. Section 3 describes the data. Section 4 performs the main empirical analysis. Section 5 is the further analyses. Section 6 concludes.

2. The impact of short-selling and margin-buying on liquidity: A framework under the limit order book

In this section, we propose a simple framework under the limit order book (LOB) to examine the effect of short-selling and/or margin-buying on liquidity with a focus on the Chinese stock market. Limit order book has emerged as a dominant trading platform for financial markets around the world, such as Euronext, Hong Kong, NYSE, NASDAQ, Paris, Stockholm, Swiss, Taiwan, Tokyo and Toronto, etc. Trading at both Shanghai and Shenzhen stock exchanges in China is also based on a centralized electronic limit order book. In the limit order markets, orders submitted by traders have clear implications on liquidity. Market order (MO) is executed immediately upon the order arrival and represents the demand for liquidity. Limit order (LO) is placed on the limit order book and executed in queue according to time and price priority and represents provision of liquidity to other traders. Thus, limit order book provides a simple framework to examine the effect of short-selling and margin-buying on liquidity. In addition, since price impact is mainly determined by the depth of limit orders at the best quotes, limit order book also offers a simple framework to analyze the price impact of short-selling and margin-buying. Price impact is not only one of the most important dimensions of liquidity but also the main measure of liquidity, namely the Amihud (2002) illiquidity ratio, used in our empirical analysis.

We assume that there are n risk-averse investors trading on a single risky asset (e.g., stock) in a limit order market. Traders are classified into two types: informed traders who possess superior information about the asset's valuation (Bagehot, 1971; Grossman and Stiglitz, 1980) and uninformed traders whose trades are motivated by liquidity or noise (Bagehot, 1971; Kyle, 1985; Black, 1986; Admati and Pfleiderer, 1988). Noise trading of uninformed traders is essential to the existence of a liquid market (Black, 1986). Following Kyle (1985), we assume that uninformed traders (n_U) are more than informed traders (n_I), i.e., $n_U > n_I$. Limit order book is characterized by a discrete set of prices ($B = \left\{B^i\right\}_{i=1}^{+\infty}$ denotes bid prices and $A = \left\{A^i\right\}_{i=1}^{+\infty}$ denotes ask prices) at which traders may submit orders. The tick size is normalized to one. Associated with bid (ask) price $B^i(A^i)$ at time t is a backlog of outstanding orders $d^i_B(d^i_A)$ called depth. A positive quantity denotes buy orders and a negative quantity denotes sell orders. Time is divided into two periods, indexed by$t = 0, 1$, where $t = 0$ denotes the initial state of the market. Fig. 1 depicts the limit order book under a normal market condition where short-selling and margin-buying are both prohibited at period $t = 0$. The exact shape of the limit order book is determined by whether market participants submit more aggressive or more conservative orders. Short-selling and/or margin-buying was allowed at period $t = 1$ with other things being equal.

In a static framework, prevailing market participants are not affected by the lift of restrictions on short-selling/margin-buying. In this case, short-selling/margin-buying will have a positive effect on the sell/buy side liquidity as short-sellers/margin-buyers' limit orders add depth to the limit order book on the sell/buy side, but a negative effect on the buy/sell side as short-sellers/margin-buyers' market orders consume limit orders at the best bid/ask, as shown in Fig. 2(a)/(b). As a result, the net effect on the depth at the best bid or ask is determined by limit and market orders submitted by short-sellers and margin-buyers.

In a dynamic framework, existing market participants react to orders submitted by short-sellers because short-sellers are generally considered to be informed (e.g., Asquith et al., 2005; Boehmer and Wu, 2013; Diamond and Verrecchia, 1987; Diether et al., 2009). In comparison, margin-buyers are shown to be less informed (Hirose et al., 2009; Kahraman and Tookes, 2017). Empirical studies show that in the Chinese stock market short-sellers possess superior information (Chang et al., 2014; Chen et al., 2016; Meng et al., 2017), while margin-buying does not have predictive power for future returns (Chang et al., 2014). Informed trading has an adverse effect on liquidity due to adverse selection caused by information asymmetry (Guerrieri and Shimer, 2014; Chang, 2018). To avoid being taken advantage by informed traders, uninformed traders may trade less or even stop trading (Ausubel, 1990; Bhattacharya and Spiegel, 1991). The adverse selection may lead to deteriorated liquidity as a result of uninformed traders withdrawing limit orders. The effect tends to be stronger for uninformed traders who place aggressive limit orders because their orders may be executed or

[4] http://legal.people.com.cn/n/2015/0709/c42510-27278103.html

[5] http://www.sse.com.cn/aboutus/mediacenter/hotandd/c/c_20150912_3988871.shtml http://www.szse.cn/disclosure/notice/general/t20150901_501533.html

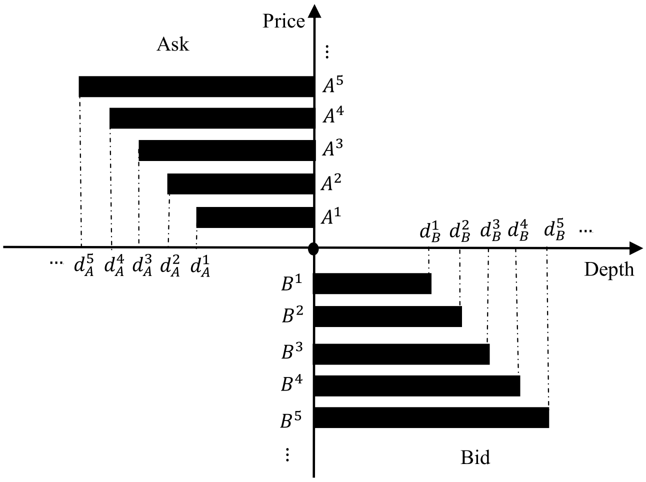

Fig. 1. Limit order book at $t = 0$.

picked off at an unfavorable price if the asset value moves against them due to the arrival of new information. This is often referred to in the literature as the "picking-off" risk (Hollifield et al., 2006; Yamamoto, 2014). The picking-off risk is particularly relevant for investors who buy shares from short-sellers. These positions may suffer imminent big losses.

Fig. 2 shows that the adverse selection has a clear effect on the depth of limit order book. In particular, the decrease of limit orders (or depth) at the best quotes has a direct effect on the price impact of trading. As an illustration, we denote the quantity of limit orders consumed by short-sellers' market orders at best bid price (B^1) as q^M and the amount of limit orders being withdrawn at B^1 as q^W. The size of market sell orders needed to push the price down a tick size is no less than d_B^1 at period$t = 0$, and is no less than $(d_B^1 - q^M)$ in the static framework at period $t = 1$, and is no less than $(d_B^1 - q^M - q^W)$ in the dynamic framework at period $t = 1$. Thus, the price impacts are $\frac{1}{d_B^1}$, $\frac{1}{d_B^1 - q^M}$, and $\frac{1}{d_B^1 - q^M - q^W}$, respectively. Since $\frac{1}{d_B^1} < \frac{1}{d_B^1 - q^M} < \frac{1}{d_B^1 - q^M - q^W}$, allowing short-selling in the dynamic framework has the largest price impact, which leads to deteriorated liquidity.

Our predictions are consistent with the literature on information asymmetry. Many studies have shown that a higher level of information asymmetry between informed and uninformed traders leads to wider spreads and lower depth (e.g., Kyle, 1985; Easley and O'Hara, 1987; Cheng et al., 2006). Hasbrouck (1991) documents that the magnitude of price impact for a given trade size is determined by the extent of information asymmetry and the proportion of uninformed traders. Since the Chinese stock market is characterized as having strong information asymmetry and a high proportion of uninformed traders, we predict that short-selling and margin-buying have a significantly negative effect on liquidity.

The above prediction also has a direct implication on the cross-sectional differences in the effect of short-selling and margin-buying on liquidity. Given that the adverse selection by uninformed traders is more pronounced for firms with high information asymmetry, we predict that the negative effect of short-selling and margin-buying on liquidity is stronger for stocks with high information asymmetry.

As noted above, the positive effect of allowing short-selling and margin-buying on liquidity is due to the limit orders placed by short-sellers and margin-buyers, whereas the negative effect is due to two reasons: one is market orders placed by short-sellers and margin-buyers, and the other is adverse selection caused by private information in short-selling. In August 2015, the Chinese stock market introduced a unique restriction on short-selling, i.e., the "T+1" trading rule. As a result, short-selling activities are drastically reduced. In this case, we predict that the negative effect of short-selling on liquidity may be dominated by the positive effect of margin-buying on liquidity since the adverse effect of short-selling is significantly weakened. We further explore the effect of the "T+1" trading rule in our empirical analysis in Section 5.2.

3. Data

Both short-selling and margin-buying were prohibited in the Chinese stock market before March 2010. The CSRC launched a pilot scheme on 31 March 2010, allowing qualified investors to buy a designated list of 90 stocks on margin and to sell them short. The list of designated stocks was expanded and revised subsequently. Table 1 presents information on the date of major expansions and revisions and the number of stocks on the designated list. From March 2010 to December 2016, there are six major expansions and revisions on March 31, 2010, December 5, 2011, January 31, 2013, September 16, 2013, September 22, 2014, and December 12, 2016. The designated list covered 950 stocks from different industries by December 2016, accounting for almost one third of the total number of A-shares listed in the Shanghai and Shenzhen stock exchanges. Table 2 Panel A presents the characteristics of the six batches of stocks added to the short-selling and margin-buying list.

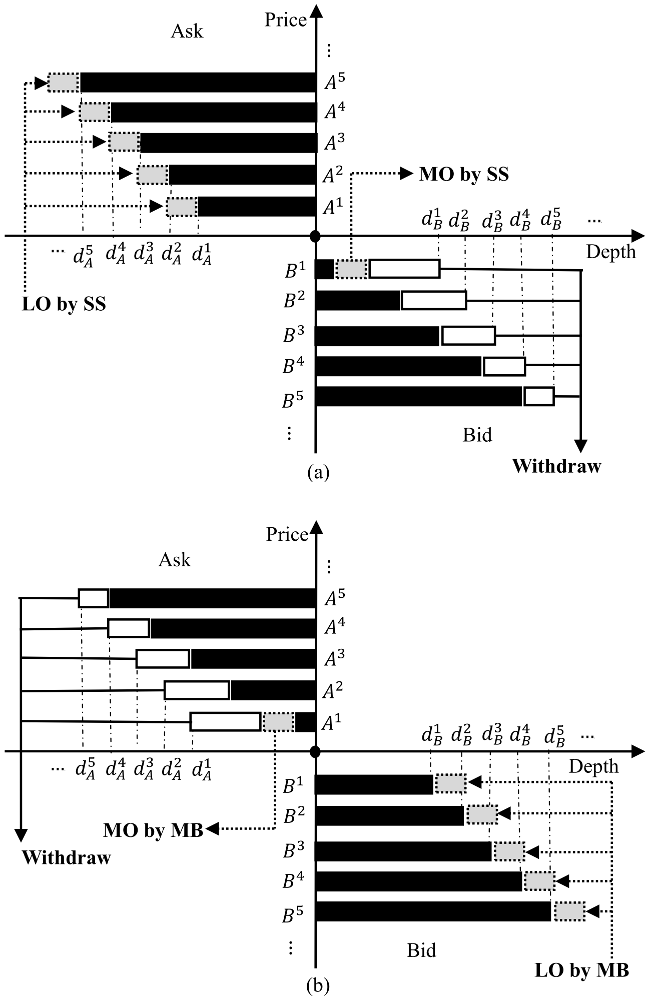

Fig. 2. Limit order book at $t = 1$.

Table 1
Major revisions of short-selling and margin-buying list in the chinese stock market.

Batch	Announcement date	Effective date	No. added	No. removed	No. on the list
1st	2010/2/12	2010/3/31	90	0	90
2ed	2011/11/25	2011/12/5	189	1	278
3rd	2013/1/25	2013/1/31	276	54	500
4th	2013/9/6	2013/9/16	206	6	700
5th	2014/9/12	2014/9/22	218	18	900
6th	2016/12/2	2016/12/12	77	27	950
Cumulated			1056	106	950

This table presents the information on the major revisions of short-selling and margin-buying list in the Chinese stock market. There are six batches of stocks added to the list in total. The regulatory agency bulletins the list of eligible stocks on *Announcement date* and allows them to sell short and buy on margin on the *Effective date*. *No. added* reports the number of stocks added to the list at each announcement. *No. removed* reports the number of stocks removed from the list between two announcement dates. *No. on the list* reports the number of stocks remaining on the list.

We manually collect information on the designated stock list from the websites of Shanghai and Shenzhen stock exchanges.[6] Data on stocks' closing price, trading volume, market capitalization, common shares outstanding, risk-free rate, and Fama–French (1993) three factors (i.e. RMRF, SMB, and HML) are obtained from the China Stock Market Trading Research (CSMAR) database.[7]

[6] Source: http://www.sse.com.cn/disclosure/magin/announcement/ and http://www.szse.cn/main/disclosure/rzrqxx/ywgg/.

[7] The China Stock Market Trading Research (CSMAR) database is provided by GuoTaiAn (GTA) Company.

Table 2
Summary statistics.

Panel A: Characteristics of the stocks added to the short-selling and margin-buying list								
Batch	No. added	No. from SHMB	No. from SZMB	No. from SMEB	No. from GE	Size (millions ¥)	Volatility (%)	Turnover (%)
1st	90	*50*	*36*	*4*	*0*	80,482.058	1.867	2.458
2ed	189	*130*	*45*	*14*	*0*	16,701.290	1.057	2.154
3rd	276	*163*	*55*	*52*	*6*	6,746.135	2.532	2.712
4th	206	*104*	*17*	*57*	*28*	5,881.743	2.972	3.383
5th	218	*104*	*35*	*55*	*24*	6,959.856	1.947	2.437
6th	77	*40*	*23*	*13*	*1*	13,091.921	1.585	1.928

Panel B: Sample selection	
Total number of stocks	1056
Stocks with missing value of Amihud ratio in either the pre- or post-event window	−22
Stocks in final sample	1034

Panel C: Matching statistics									
	N	Lnsize	Turnover	Volatility		N	Lnsize	Turnover	Volatility
Treated	1034	22.826	2.277	2.633	Treated	1034	22.826	2.277	2.633
Untreated	9921	21.533	2.639	2.532	Control	1034	22.045	2.256	2.590
Diff $^{T-U}$		1.293***	−0.362***	0.101**	Diff $^{T-C}$		0.781***	0.021	0.043
		(47.07)	(−4.48)	(2.37)			(26.25)	(0.19)	(1.12)

This table describes sample selection and matching procedure. **Panel A** presents the characteristics of the six batches of stocks added to the short-selling and margin-buying list. For each batch, *No. added* is the total number of stocks added to the list. *No. from SHM*, *No. from SZM*, *No. from SME*, and *No. from GEM* are the amount of stocks added to the list from the Shanghai main board, the Shenzhen main board, the small and medium-sized enterprise board, and the growth enterprise market. *Size* is the average of market capitalization over the previous quarter before the effective date denoted in millions of RMB. *Volatility* is the standard deviation of daily raw returns over the previous quarter before the effective date denoted in percentage. *Turnover* is the average of daily turnover over the previous quarter before the effective date denoted in percentage. **Panel B** illustrates the sample selection procedure. We begin with all stocks that are allowed short-selling and margin-buying of the six major addition revisions. The stocks are required to have at least 30 observations in either the pre- or post-event window. **Panel C** reports a comparison of treated stocks with untreated stocks and matched control stocks. For each treated stock, we choose with replacement the untreated stock that is listed on the same exchange and has the smallest distance measure. The distance metric is the sum of the percentage differences between the untreated match candidate and the treated stock in market capitalization, turnover, and volatility over the matching window (i.e., three months before the event date). We present the mean of log market capitalization, turnover and volatility for untreated, treated and control groups, as well as their mean differences and *t*-statistics (in parentheses).

Analysts' earnings forecasts data is downloaded from Wind Information Inc. (WIND), the largest and most prominent financial data provider in China.[8]

As shown in Table 1, there are a total of 1056 additions to the designated list, of which 106 stocks are removed from the list subsequently.[9] In this paper, we focus on the change of liquidity for stocks that are added to the designated list for margin-buying and short-selling. The sample size in our empirical test is reduced by 22 due to missing value of Amihud measure in either the pre- or the post-event window. Thus, there are 1034 stock additions in our sample. Our sample period spans from October 2009 to June 2017. The long sample period helps reduce the confounding impact of market events.

4. The impact of short-selling and margin-buying on liquidity: Empirical analysis

4.1. Main empirical analysis

We employ the difference-in-differences (DID) approach, which has been used extensively in studies of regulatory change in economics, law and finance, to test the effect of short-selling and margin-buying on liquidity. Our treated group consists of stocks that are added to the short-selling and margin-buying list. There are 1034 stocks in the treated sample. We create a matched control sample of 1034 stocks which are banned for short-selling and margin-buying. Similar to Beber and Pagano (2013) and Boehmer et al. (2013), sample stocks are matched by listing exchange, market capitalization, turnover, and volatility over the matching window (i.e., three months before the effective date). The distance metric is the sum of the percentage differences between the untreated match candidate and the treated stock in market capitalization, turnover, and volatility. For each treated stock, we choose with replacement the untreated stock with the same listing exchange and the smallest distance. Since the eligible stocks are mainly the large and liquid Chinese firms, in order to avoid comparing these stocks with the small and illiquid untreated stocks, we allow stocks added to the list later to be selected as controls for stocks added to the list earlier in the sample period. We acknowledge that the control group may be subject to potential indirect or spillover effect of the pilot program. For details and an empirical analysis of the spillover effect, please refer to (Boehmer et al., 2019).

[8] WIND serves 90% of China's financial institutions and 70% of the Qualified Foreign Institutional Investors (QFII) operating in China.

[9] According to the implementation rules promulgated by the Shanghai and Shenzhen stock exchanges, a stock is removed from the designated list mainly because it has been warned to be risky. These stocks have typically had very low trading volume and/or high return volatility. Therefore, it is challenging to study the impact on liquidity when restrictions on margin-buying and short-selling are re-imposed on these stocks.

Table 3
The impact of short-selling and margin-buying on liquidity: univariate analysis.

Group	N	Amihud illiquidity ratio		
		Before	After	$Diff^{A-B}$
Untreated	9921	0.823	0.746	−0.077** (−2.15)
Treated	1031	0.275	0.222	−0.053*** (−5.09)
Control	1031	0.626	0.490	−0.136*** (−4.45)
$Diff^{T-C}$	1031	−0.351*** (−13.87)	−0.268*** (−19.31)	0.083*** (2.87)

The table reports the results of the univariate analysis about the impact of short-selling and margin-buying on liquidity. *N* is the number of stocks in untreated, treated and control groups. A stock's Amihud illiquidity ratio is calculated as the absolute value of daily stock return divided by the trading volume in RMB scaled by 10^9 and then averaged over 120 trading days in the pre- or post-event window. The means of stocks' Amihud illiquidity ratio before/after the event in untreated, treated, and control groups are reported in column *Before/After*. *Diff* $^{T-C}$ is the mean of pairwise difference in Amihud illiquidity ratio between treated and control stocks. *Diff* $^{A-B}$ is the mean difference in Amihud illiquidity ratio before and after the event for untreated, treated, and control groups as well as *Diff* $^{T-C}$. *t* statistics are in the parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel C of Table 2 reports the quality of matching procedure. The treated stocks differ significantly from untreated stocks in market capitalization, turnover, and volatility. Specifically, the mean difference in the log of market capitalization, turnover, and volatility between treated and untreated groups are 1.293 (t-stat = 47.07), −0.362 (t-stat = −4.48), and 0.101 (t-stat = 2.37), respectively. The mean difference in turnover and volatility between treated and control groups becomes insignificant, while the mean difference in the log of market capitalization still remains significant at all levels, but narrows greatly (i.e., 0.781 with t-stat = 26.25). To address this issue, we also include market capitalization as a control variable in the multivariate regression.

In Section 2, we predict that short-selling and margin-buying have a significantly negative effect on liquidity in the Chinese stock market where information asymmetry is strong and the proportion of uninformed traders is high. We apply the DID methodology to test for the effect of short-selling and margin-buying on liquidity over a window of 120 days. Event date is the effective date when restrictions on short-selling and margin-buying are lifted. We use Amihud (2002) illiquidity ratio to measure price impact, which is calculated as the absolute value of daily stock return divided by the trading volume in RMB scaled by 10^9 and then averaged over a 120-day period.

The DID results are reported in Table 3. The mean of Amihud illiquidity ratio for stocks in the untreated group is 0.823 over the pre-event window and is 0.746 over the post-event window. The mean of Amihud illiquidity ratio for stocks in the treated group is 0.275 over the pre-event window and is 0.222 over the post-event window. The mean of Amihud illiquidity ratio for stocks in the control group is 0.626 over the pre-event window and is 0.490 over the post-event window. The differences in Amihud illiquidity ratio before and after the event (i.e., *Diff* $^{A-B}$ in Table 3) are, respectively, −0.077 (t-stat = −2.15), −0.053 (t-stat = −5.09), and −0.136 (t-stat = −4.45) for the untreated, treated, and control groups, which are all significantly different from zero at 5% level. The mean of difference in Amihud liquidity ratio between treated stocks and matched control stocks (i.e., *Diff* $^{T-C}$ in Table 3) are significantly negative at 1% level in both the pre- and post-event windows, which means that treated stocks are more liquid than control stocks. The difference in differences of Amihud liquidity ratio before and after the event between the treated and control groups is 0.083 with t-stat = 2.87, significantly different from zero at all conventional significance levels. Therefore, while there is a significant improvement of liquidity for stocks in the treated group during the post-event period than during the pre-event period, the improvement of liquidity for stocks in the treated group is significantly lower than those stocks in the control group. This is evidence of a significantly negative effect of short-selling and margin-buying on liquidity.

We also perform the following regression to investigate the impact of short-selling and margin-buying on liquidity:

$$y_{i,T} = \alpha + \beta_1 Post_T + \beta_2 Treated_i + \beta_3 Post_T * Treated_i + \varepsilon_{i,T} \tag{1}$$

where $y_{i,T}$ is the variable of interest of stock i at time T ($T = 0$ represents before the event and $T = 1$ after the event). $Post$ is an indicator variable set equal to one if the restrictions on short-selling and margin-buying are lifted. $Treated$ is also an indicator variable set equal to one if stock i is added to the short-selling and margin-buying list.

As noted earlier, there is a significant difference in market capitalization for stocks in the treated and matched control groups as shown in Panel C of Table 2. We further perform the following regression to ensure that the above result is not driven by the differences in stock characteristics between the treated and control groups.

$$y_{i,T} = \alpha + \beta_1 Post_T + \beta_2 Treated_i + \beta_3 Post_T * Treated_i + \gamma Control + \varepsilon_{i,T} \tag{2}$$

where $Control$ includes the log of market capitalization ($LnSize$), turnover ($Turnover$) and volatility ($Volatility$) over the previous quarter before the event.

The results of regressions (1) and (2) are presented in Table 4. In specification ① of Table 4, the coefficient of $Post$ is −0.135 (t-stat = −5.10), indicating that stocks experience a significant increase in liquidity after the event. The coefficient of $Treated$ is

Table 4
The impact of short-selling and margin-buying on liquidity.

Explanatory variable	Dependent variable: Amihud illiquidity ratio			
	①	②	③	④
Post	−0.135*** (−5.10)	−0.135*** (−5.10)	−0.135*** (−5.10)	−0.135*** (−5.10)
Treated	−0.351*** (−13.86)	−0.268*** (−12.68)	−0.243*** (−10.28)	−0.236*** (−10.56)
Post*Treated	0.083*** (3.24)	0.083*** (3.23)	0.083*** (3.23)	0.083*** (3.23)
LnSize		−0.123*** (−9.58)	−0.162*** (−13.51)	−0.172*** (−8.95)
Turnover			−0.050*** (−6.15)	−0.046*** (−5.63)
Volatility			0.075*** (4.64)	0.064** (2.38)
Time FE	No	No	No	Yes
Intercept	0.626*** (23.02)	3.344*** (11.10)	4.120*** (14.63)	4.328*** (9.86)
N	4124	4124	4124	4124
Adj. R^2	0.090	0.135	0.158	0.174

This table reports the results of regressions (1) and (2). The variable of interest is Amihud illiquidity ratio, which is the average of stock i's daily Amihud illiquidity ratio over 110 trading days in the pre-event window ($t \in [-120, -11]$ where $T = 0$) or post-event window ($t \in [11, 120]$ where $T = 1$) with at least 30 observations. Stock i's daily Amihud illiquidity ratio is calculated as the absolute value of daily stock return divided by the trading volume in RMB scaled by 10^9. *Post* is an indicator variable set equal to one if the short-selling and margin-buying restrictions are lifted. *Treated* is also an indicator variable set equal to one if stock i is added to the short-selling and margin-buying list. The control variables are the same as in Table 4. The t statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, using standard errors clustered at the batch × stock level.

−0.351 (t-stat = −13.86), which means that treated stocks are more liquid than control stocks. The coefficient of $Post * Treated$ is 0.083 with t-stat = 3.24, which is consistent with the result in Table 3. It suggests that lifting restrictions on short-selling and margin-buying has a negative impact on liquidity. The coefficient of $Post * Treated$ remains significantly positive at 1% level when market capitalization, turnover, volatility, and the time fixed effect are controlled. Consistent with existing literature, there is a positive relation between market capitalization and liquidity and a negative relation between turnover and Amihud illiquidity ratio.

As shown in Table 3, there is generally a downward trend in Amihud illiquidity for the whole market, including both treated and control groups. One potential concern for our main finding is that the treated group and control group may have different trends. The less significant drop in Amihud illiquidity for the treated group, relative to the control group, over the post-event period may be an artifact that control stocks, which are less liquid, have more room for liquidity improvement in an environment where liquidity is generally improving. To address this concern, we examine the pre- and post-trends of Amihud illiquidity ratio for both treated and control groups. As shown in Panel A of Table 5, there is no significant difference in beta estimates of the treated and control groups during both the period prior to the pre-event window and the pre-event window, which indicates that the treated and control groups have common trends in liquidity before the event. In Panel B, we also report the differences in the intercept between the treated and control groups during the post-event window as well the difference in differences. The difference in differences of the estimates of the intercept before and after the event between the treated and control groups is significantly positive at 0.0437 (t-stat = 2.73), consistent with our main findings.

While it is not surprising to see the insignificant difference in illiquidity trends between the treated group and control group over the pre-event window, the insignificant difference in illiquidity trends over the post-event window seems to suggest that margin-buying and short-selling have an immediate effect on liquidity. To further understand how the Amihud illiquidity changes over the post-event window, we replicate the main analysis in Table 3 by changing the post-event window to 30 trading days and 60 trading days. The results are reported in Table 6 where the pre-event window remains unchanged (i.e., $t \in [-120, -1]$. In Panel A where the post-event window is 30 trading days after the event date (i.e., $t \in [1, 30]$), the difference in differences of Amihud illiquidity ratio before and after the event between the treated and control groups is 0.069 (t-stat = 2.17). In Panel B where the post-event window is 60 trading days after the event date (i.e., $t \in [1, 60]$), the difference in differences of Amihud illiquidity ratio before and after the event between the treated and control groups is 0.096 (t-stat = 3.29). Recall that in Table 3 where the post-event window is 120 trading days after the event date (i.e., $t \in [1, 120]$), the difference in differences of Amihud liquidity ratio before and after the event between the treated and control groups is 0.083 (t-stat = 2.87). The results show an inverted U-shaped pattern for the impact of short-selling and margin-buying on liquidity. That is, the negative impact on liquidity intensifies initially but moderates afterwards. This also explains why the beta estimates are insignificantly different for the treated and control groups during the 120-day post-event window (i.e., $t \in [1, 120]$).

Table 5
Trends of amihud lliquidity ratio: pre- and post-event windows.

Panel A: Estiamtes of β over pre- and post-event windows			
Group	Period prior to pre-event window $t \in [-240, -121]$	Pre-event window $t \in [-120, -1]$	Post-event window $t \in [0, 120]$
Control	−0.0004 (−0.56)	−0.0020*** (−3.80)	−0.0002 (−0.61)
Treated	−0.0001 (−0.14)	−0.0016*** (−9.42)	−0.0001 (−0.37)
Diff $^{T-C}$	0.0003 (0.22)	0.0004 (0.97)	0.0001 (0.65)

Panel B: Estimates of α over pre- and post-event windows				
Group	Period prior to pre-event window $t \in [-240, -121]$	Pre-event window $t \in [-120, -1]$	Post-event window $t \in [0, 120]$	Diff $^{A-B}$
Control	0.6153*** (4.73)	0.4885*** (13.02)	0.4935*** (22.60)	0.0050 (0.21)
Treated	0.4017** (2.12)	0.1739*** (14.68)	0.2226*** (21.96)	0.0487*** (6.68)
Diff $^{T-C}$	−0.2136 (−0.99)	−0.3146*** (−9.87)	−0.2709*** (−18.31)	0.0437*** (2.73)

This table reports the results of the following regression during the 120 trading days prior to pre-event window, the 120 trading days during pre-event window, and the 120 trading days during post-event window:

$$Amihud_t = \alpha + \beta * t + \varepsilon_t$$

where $Amihud_t$ is the average of Amihud ratio of all stocks in the control or treated group on day t. The estimated β over different event windows as well as the differences in β between treated and control groups are reported in **Panel A**. The estimated α over different event windows, the differences in α between treated and control groups, and the difference in differences of α before and after the event between the treated and control groups are reported in **Panel B**. The t statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level.

Table 6
The impact of short-selling and margin-buying on liquidity over different event windows.

Group	N	Before	After	Diff^{A-B}
Panel A: Results based on 30-day post-event window ($t \in [0, 30]$)				
Treated	1006	0.274	0.235	−0.039***
Control	1006	0.622	0.514	−0.108***
Diff^{T-C}	1006	−0.348*** (−13.53)	−0.279*** (−14.57)	0.069** (2.17)
Panel B: Results based on 60-day post-event window ($t \in [0, 60]$)				
Treated	1005	0.274	0.221	−0.053***
Control	1005	0.624	0.475	−0.149***
Diff^{T-C}	1005	−0.350*** (−13.59)	−0.254*** (−18.40)	0.096*** (3.29)

The table reports the trend of the impact of short-selling and margin-buying on liquidity. N is the number of stocks in treated and control groups. *Before* reports the means of stocks' Amihud illiquidity ratio, calculated as the absolute value of daily stock return divided by the trading volume in RMB scaled by 10^9 and then averaged over 120 trading days (with at least 30 observations) over the pre-event window. *After* reports the means of stocks' Amihud illiquidity ratio, calculated as the absolute value of daily stock return divided by the trading volume in RMB scaled by 10^9 and then averaged over 30 or 60 trading days (with, respectively, at least 7 and 15 observations) over the post-event window. The results for 30- and 60-day post-event window are reported in **Panels A and B**, respectively. *Diff* $^{T-C}$ is the mean of pairwise difference in Amihud illiquidity ratio between treated and control stocks. *Diff* $^{A-B}$ is the mean difference in Amihud illiquidity ratio before and after the event for treated and control groups as well as *Diff* $^{T-C}$. t statistics are in the parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Consistent with our theoretical prediction in Section 2, the above empirical results show that lifting restrictions on short-selling and margin-buying has a negative impact on liquidity in the Chinese stock market. Existing literature has shown that short-sellers in the Chinese stock market are better informed (e.g., Chang et al., 2014; Chen et al., 2016). When restrictions on short-selling and margin-buying are lifted, more informed traders, i.e., short-sellers, participate in the market. Uninformed traders thus run higher risk of being picked off, especially when they submit limit orders at best quotes. The adverse selection by uninformed traders may lead to deteriorated liquidity as a result of withdrawing limit orders at best quotes.

Our findings are consistent with Sharif et al. (2014). Based on a sample of 90 stocks of the pilot scheme in 2010, they find that the bid–ask spread of treated stocks increases when restrictions on short-selling and margin-buying are lifted in the Chinese

Table 7
The impact of short-selling and Margin-Buying on liquidity: Skip days between announcement date and effective date.

Explanatory variable	Dependent variable: Amihud illiquidity ratio			
	①	②	③	④
Post	−0.156*** (−5.08)	−0.156*** (−5.07)	−0.156*** (−5.07)	−0.156*** (−5.07)
Treated	−0.369*** (−12.97)	−0.279*** (−12.01)	−0.257*** (−9.74)	−0.254*** (−10.35)
Post*Treated	0.093*** (3.17)	0.093*** (3.17)	0.093*** (3.17)	0.093*** (3.17)
LnSize		−0.135*** (−8.90)	−0.168*** (−13.26)	−0.173*** (−8.24)
Turnover			−0.047*** (−5.33)	−0.044*** (−4.88)
Volatility			0.078*** (4.49)	0.069** (2.24)
Time FE	No	No	No	Yes
Intercept	0.652*** (21.16)	3.632*** (10.20)	4.260*** (14.42)	4.362*** (9.19)
N	4096	4096	4096	4096
Adj. R^2	0.081	0.125	0.142	0.153

This table reports the results of regressions (1) and (2). The variable of interest is Amihud illiquidity ratio, which is the average of stock i's daily Amihud illiquidity ratio over 110 trading days in the pre-event window ($t \in [-120, -11]$ where $T = 0$) or post-event window ($t \in [11, 120]$ where $T = 1$) with at least 30 observations. Stock i's daily Amihud illiquidity ratio is calculated as the absolute value of daily stock return divided by the trading volume in RMB scaled by 10^9. *Post* is an indicator variable set equal to one if the short-selling and margin-buying restrictions are lifted. *Treated* is also an indicator variable set equal to one if stock i is added to the short-selling and margin-buying list. The control variables are the same as in Table 4. The t statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, using standard errors clustered at the batch × stock level.

stock market. However, our empirical analysis focuses on the price impact dimension of liquidity and is performed over an extended sample period from 2010 to 2016. This not only enhances the power of our analysis but also allows us to examine one unique feature in the Chinese stock market, namely the "T+1" trading rule imposed on short-selling in 2015 (see Section 5.2). Our findings are in contrast with some studies on the developed markets (such as, Marsh and Payne, 2012; Beber and Pagano, 2013; Boehmer et al., 2013 etc.) We note that the policy changes on short-selling in developed markets usually occur during crisis periods, when stock liquidity is intensively affected by other aggregate factors. However, the pilot program in the Chinese stock market is conducted during a period with normal market conditions.

4.2. Robustness checks

As shown in Section 4.1, there is a significantly negative effect of allowing short-selling and margin-buying on liquidity in the Chinese stock market. In this section, we examine whether the negative impact is robust to variations of event windows or different matching method used in constructing the control group. We also perform placebo test to investigate the potential of other omitted variables to confound our results.[10]

4.2.1. Skip days between announcement date and effective date

The Shanghai and Shenzhen stock exchanges bulletin the list of eligible stocks on announcement date and allows them to sell short and buy on margin on the effective date. Generally, the announcement date is about 10 days before the effective date, except the first batch of pilot stocks, as can be seen in Table 1. As the effective date is known to the public on announcement date, investors may take action accordingly in advance. Chang et al. (2014) find that the abnormal return cumulated during the five trading days before the event is significantly negative, indicating that investors' selling activities in advance may push the pre-event price drop. It is likely that investors' reactions may affect liquidity as well. Therefore, we skip the 10 trading days before and after the event date (i.e., pre-event window: $t \in [-120, -11]$; post-event window: $t \in [11, 120]$) to have a clean evaluation of the impact of short-selling and margin-buying on liquidity. The results are reported in Table 7. The coefficient of $Post * Treated$ is 0.093 with t-stat = 3.17, significant at 1% level in specification ① of Table 7. The result remains significant at all levels when market capitalization, turnover, volatility, and time fixed effect are included. Thus, the negative impact of short-selling and margin-buying on liquidity remains significant in a cleaner event window.

[10] We wish to thank the referee and the Associate Editor for the suggestion of performing placebo test.

Table 8
The impact of short-selling and Margin-Buying on liquidity: Different matching method.

Explanatory Variable	Dependent variable: Amihud illiquidity ratio			
	①	②	③	④
Post	−0.105*** (−7.31)	−0.105*** (−7.30)	−0.105*** (−7.30)	−0.105*** (−7.30)
Treated	−0.208*** (−12.68)	−0.178*** (−11.00)	−0.169*** (−9.85)	−0.179*** (−10.09)
Post*Treated	0.053*** (3.29)	0.053*** (3.28)	0.053*** (3.28)	0.053*** (3.28)
LnSize		−0.121*** (−13.57)	−0.163*** (−15.23)	−0.119*** (−8.30)
Turnover			−0.029*** (−5.69)	−0.019*** (−3.67)
Volatility			5.133*** (4.01)	2.757* (1.70)
Time FE	No	No	No	Yes
Intercept	0.488*** (33.52)	3.219*** (15.67)	4.101*** (16.18)	3.032*** (8.79)
N	3908	3908	3908	3908
Adj. R^2	0.078	0.138	0.167	0.195

In this table, we apply standard propensity score matching method. The score is computed by estimating the logistic regression (3). Each treated stock is matched with a stock in the untreated group that has the closest score without replacement. This table reports the results of regressions (1) and (2). The variable of interest is Amihud illiquidity ratio, which is the average of stock i's daily Amihud illiquidity ratio over 120 trading days in the pre-event window ($t \in [-120, -1]$ where $T = 0$) or post-event window ($t \in [1, 120]$ where $T = 1$) with at least 30 observations. Stock i's daily Amihud illiquidity ratio is calculated as the absolute value of daily stock returns divided by the trading volume in RMB scaled by 10^9. *Post* is an indicator variable set equal to one if the short-selling and margin-buying restrictions are lifted. *Treated* is also an indicator variable set equal to one if stock i is added to the short-selling and margin-buying list. The control variables are the same as in Table 4. The t statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, using standard errors clustered at the batch × stock level.

4.2.2. Different matching method

We apply the standard propensity score matching technique to match control stocks, where the score is computed by estimating the following logistic regression:

$$Treated_i = \alpha + \theta_1 LnSize_i + \theta_2 Turnover + \theta_3 Volatility_i + \epsilon_i \tag{3}$$

We use the estimates of this logistic regression to compute the probability (the "score") that a stock is added to the designated list given its market capitalization, turnover, and volatility. Then, we match each treated stock with stock in the untreated group that has the closest score without replacement. The sample reduces to 977 stock additions due to unmatched control. The regression results are reported in Table 8. The coefficient of $Post * Treated$ is 0.053 with t-stat = 3.29, which is robust to including control variables and time fixed effect. This is evidence that the negative effect of short-selling and margin-buying on liquidity is robust to different matching method.

4.2.3. Placebo test

To further control for potential confounding effects or omitted variables, we perform a placebo test. A placebo test uses a different sample that does not have access to the treatment (Angrist and Krueger, 1999; Balakrishnan et al., 2014). In our setting, the treatment in question is the lift of restrictions on short-selling and margin-buying for stocks on the designated list and the treatment effect is a deterioration in liquidity. If we observe the same treatment effect in the placebo group as in the treated stocks, we would infer that the treatment is unlikely to have caused the observed treatment effect (i.e., liquidity deterioration).

To implement the placebo test, we use stocks in the control group (see Panel C of Table 2) as the placebo group and construct a matched control group the same way as described in Section 4.1. Specifically, stocks in the placebo group are matched with the rest of untreated stocks that trade in the same exchange and is closest in terms of market capitalization, turnover, and volatility. The placebo test results are presented in Table 9. The coefficient of $Post$ is significantly negative as in the main Table 4, indicating that stocks experience a significant increase in liquidity after the event. However, the coefficient of $Post * Treated$ is −0.040 with t-stat = -1.33, which is negative and statistically insignificant. The results are consistent with our prediction that uninformed traders who trade on the treated stocks face the risk of having their limit orders being picked off by informed traders, i.e., short-sellers. As a result, they may withdraw their orders, especially those at best quotes, leading to deteriorated liquidity of treated stocks. On the other hand, the uninformed traders who trade on the untreated stocks do not face the risk of trading against informed short-sellers, so stock liquidity is not affected.

Table 9
Placebo test.

Explanatory variable	Dependent variable: Amihud illiquidity ratio			
	①	②	③	④
Post	−0.096*** (−5.21)	−0.096*** (−5.21)	−0.096*** (−5.21)	−0.096*** (−5.20)
Treated	−0.029 (−1.02)	0.002 (0.06)	0.015 (0.51)	0.016 (0.56)
Post*Treated	−0.040 (−1.33)	−0.040 (−1.33)	−0.040 (−1.33)	−0.040 (−1.33)
LnSize		−0.196*** (−11.88)	−0.296*** (−15.44)	−0.303*** (−11.21)
Turnover			−0.079*** (−7.43)	−0.071*** (−6.80)
Volatility			0.076*** (3.80)	0.060* (1.89)
Time FE	No	No	No	Yes
Intercept	0.655*** (36.24)	4.943*** (13.51)	7.107*** (16.05)	7.251*** (11.93)
N	4108	4108	4108	4108
Adj. R^2	0.010	0.079	0.124	0.145

This table reports the results of regressions (1) and (2) where the placebo group are stocks identified as control group in Panel C of Table 2. The control group are constructed the same way as described in Section 4.1. That is, stocks in placebo group are matched with the rest of untreated stocks that trade in the same exchange and is closest in terms of market capitalization, turnover, and volatility. The variable of interest is Amihud illiquidity ratio, which is the average of stock i's daily Amihud illiquidity ratio over 120 trading days in the pre-event window ($t \in [-120, -1]$ where $T = 0$) or post-event window ($t \in [1, 120]$ where $T = 1$). Stock i's daily Amihud illiquidity ratio is calculated as the absolute value of daily stock return divided by the trading volume in RMB scaled by 10^9. *Post* is an indicator variable set equal to one if the short-selling and margin-buying restrictions are lifted. *Treated* is also an indicator variable set equal to one if stock i is added to the short-selling and margin-buying list. The control variables are the same as in Table 4. The t statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, using standard errors clustered at the batch × stock level.

5. Further analyses

5.1. The role of information asymmetry

In this section, we empirically test the prediction in Section 2 that the negative impact of short-selling and margin-buying on liquidity is stronger for stocks with high information asymmetry. We use two proxies for information asymmetry in our empirical analysis, namely analysts' earnings forecast dispersion and idiosyncratic volatility. Analysts' earnings forecast dispersion is measured as the standard deviation of all analysts' earnings forecasts made in the past 180 days preceding the event date. Since many stocks in the sample have few or no analysts following, the sample reduces to 777 stock additions. The idiosyncratic volatility is calculated as the standard deviation of the error terms based on the Fama and French (1993) three-factor model estimated in the window of 180 trading days before the event date.[11]

We perform the following regression:

$$\begin{aligned} y_{i,T} &= \alpha + \beta_1 Post_T + \beta_2 Treated_i + \beta_3 Asym_i + \\ &\beta_4 Post_T * Asym_i + \beta_5 Treated_i * Asym_i + \beta_6 Post_T * Treated_i + \beta_7 Post_T * Treated_i * Asym_i + \\ &\gamma Control + \varepsilon_{i,T} \end{aligned} \quad (4)$$

where $Asym$ is an indicator variable set equal to one if the information asymmetry, measured by analysts' earnings forecast dispersion and idiosyncratic volatility, is above the median, respectively. β_7 is the parameter of interest. It is expected to be positive if the negative impact of short-selling and margin-buying on liquidity is more pronounced for stocks with high information asymmetry.

The results are reported in Table 10. In Panel A, the coefficient of $Post * Treated * Asym$ is 0.126, significant at 5% level in specifications ①–④, where the information asymmetry is measured by analysts' earnings forecast dispersion. In Panel B, the coefficient of $Post * Treated * Asym$ is also significantly positive in specifications ①–④, where the information asymmetry is measured by idiosyncratic volatility. That is, consistent with theoretical prediction in Section 2, the impact of short-selling and margin-buying on liquidity is indeed stronger for stocks with high information asymmetry.

[11] We also compute the idiosyncratic volatility as the standard deviation of the error terms based on the market model estimated in the same window. The results are consistent.

Table 10
The role of information asymmetry.

Explanatory variable	Dependent variable: Amihud illiquidity ratio					
	Panel A: Analysts' earnings forecast dispersion			Panel B: Idiosyncratic volatility		
	①	②	③	④	⑤	⑥
Post	−0.045* (−1.71)	−0.045* (−1.71)	−0.045* (−1.71)	−0.081*** (−4.36)	−0.081*** (−4.36)	−0.081*** (−4.36)
Treated	−0.322*** (−14.09)	−0.211*** (−9.56)	−0.215*** (−9.29)	−0.339*** (−18.57)	−0.225*** (−14.09)	−0.213*** (−10.92)
Asym	0.047 (0.91)	0.035 (0.74)	0.041 (0.87)	0.044 (0.82)	0.001 (0.02)	−0.010 (−0.25)
Post*Asym	−0.104** (−2.05)	−0.104** (−2.05)	−0.104** (−2.05)	−0.109** (−2.05)	−0.109** (−2.05)	−0.109** (−2.05)
Treated*Asym	−0.068 (−1.36)	−0.070 (−1.43)	−0.070 (−1.42)	−0.023 (−0.46)	−0.038 (−0.76)	−0.040 (−0.78)
Post*Treated	−0.008 (−0.29)	−0.008 (−0.29)	−0.008 (−0.29)	0.028 (1.58)	0.028 (1.58)	0.028 (1.58)
Post*Treated*Asym	0.126** (2.44)	0.126** (2.44)	0.126** (2.43)	0.109** (2.13)	0.109** (2.13)	0.109** (2.13)
LnSize		−0.154*** (−12.28)	−0.148*** (−8.61)		−0.160*** (−13.46)	−0.177*** (−8.76)
Turnover		−0.049*** (−4.67)	−0.040*** (−3.73)		−0.048*** (−5.98)	−0.047*** (−5.73)
Volatility		0.051*** (2.68)	0.012 (0.45)		0.085*** (5.58)	0.086*** (2.81)
Time FE	No	No	Yes	No	No	Yes
Intercept	0.574*** (24.21)	3.956*** (12.97)	3.848*** (9.27)	0.603*** (28.14)	4.044*** (14.59)	4.421*** (9.75)
N	3108	3108	3108	4124	4124	4124
Adj. R^2	0.120	0.197	0.217	0.091	0.160	0.176

This table reports the results of regression (4). The variable of interest is Amihud illiquidity ratio, which is the average of stock i's daily Amihud illiquidity ratio over 120 trading days in the pre- or post-event window with at least 30 observations. Stock i's daily Amihud illiquidity ratio is calculated as the absolute value of daily stock returns divided by the trading volume in RMB scaled by 10^9. *Post* is an indicator variable set equal to one if the short-selling and margin-buying restrictions are lifted. *Treated* is also an indicator variable set equal to one if stock i is added to the short-selling and margin-buying list. *Asym* is an indicator variable set equal to one if the information asymmetry, measured by analysts' earnings forecast dispersion in Panel A and idiosyncratic volatility in Panel B, is above the median. The control variables are the same as in Table 4. The t statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, using standard errors clustered at the batch × stock level.

5.2. The effect of "T+1" trading rule

In this section, we examine one unique feature in the Chinese stock market, i.e., the "T+1" trading rule.[12] The "T+1" trading rule prevents investors from selling stocks bought on the same day. Initially only margin-buying is subject to the "T+1" trading rule. However, short-sellers in the Chinese stock market became easy scapegoats during the market crash in June 2015. As noted in Boehmer et al. (2013), short-sellers are often blamed when share prices fall. In July 2015, the CSRC began to crackdown on "malicious short sellers" whose high-frequency trading practices were believed to be akin to market manipulation. The CSRC even fined Citic Securities, Haitong Securities, and Guosen Securities for facilitating bearish bets on the stock market during the market crash. The regulators imposed a series of restrictions on short-selling as the crash worsened. On August 3, 2015, both Shanghai and Shenzhen stock exchanges promulgated notices on modifying the implementation rules of short-selling and margin-buying. The main change is that after short sale, the client may, starting from the next trading day, repay the financed securities to the member by purchasing securities or directly repay the securities. That is, the "T+1" trading rule is also imposed on short-selling. The result of these regulatory changes is that many large security brokerages (for example, Citic Securities, Huatai Securities, and Guosen Securities, etc.) drastically reduced their short-selling business and short-selling activity decreased substantially. The average daily short volume decreased from about 1830 million shares over the 120-day period before August 3, 2015 to about 33 million shares over the 120-day period after. As conjectured in Section 2, the adverse effect of short-selling is significantly weakened and its negative effect on liquidity may be dominated by the positive effect of margin-buying on liquidity.

We take advantage of the fact that the first five batches of stock additions occurred before the regulation changes and are thus not subject to the "T+1" trading rule on short-selling, and the 6th batch of stock additions occurred after the regulation changes and are subject to the "T+1" trading rule on short-selling. We perform empirical analyses separately on the two subsamples. The results are reported in Table 11. As shown in Panel A of Table 11, the coefficient of $Post * Treated$ is 0.094 with t-stat = 3.44,

[12] We wish to thank the referee for the suggestion of examining the unique feature, i.e., the "T+1" trading rule, in the Chinese stock market.

Table 11
The effect of "T+1" trading rule.

Explanatory Variable	Dependent variable: Amihud illiquidity ratio						
	Panel A: 1st–5th Batches				Panel B: 6th Batch		
	①	②	③	④	⑤	⑥	⑦
Post	−0.152*** (−5.35)	−0.152*** (−5.35)	−0.152*** (−5.35)	−0.152*** (−5.35)	0.092*** (6.60)	0.092*** (6.58)	0.092*** (6.56)
Treated	−0.374*** (−13.87)	−0.294*** (−12.89)	−0.262*** (−10.30)	−0.253*** (−10.42)	−0.029*** (−3.73)	−0.022*** (−3.11)	−0.018*** (−2.76)
Post*Treated	0.094*** (3.44)	0.094*** (3.44)	0.094*** (3.44)	0.094*** (3.44)	−0.075*** (−4.53)	−0.075*** (−4.52)	−0.075*** (−4.51)
LnSize		−0.114*** (−8.61)	−0.160*** (−13.14)	−0.173*** (−8.46)	−0.045*** (−3.39)	−0.065*** (−6.60)	
Turnover			−0.047*** (−5.78)	−0.047*** (−5.56)		−0.057*** (−4.59)	
Volatility			0.059*** (3.16)	0.066** (2.35)		0.057*** (4.64)	
Time FE	No	No	No	Yes	No	No	No
Intercept	0.660*** (22.88)	3.164*** (10.23)	4.123*** (14.45)	4.367*** (9.33)	0.155*** (19.72)	1.189*** (3.93)	1.635*** (7.17)
N	3844	3844	3844	3844	280	280	280
Adj. R^2	0.096	0.133	0.153	0.166	0.187	0.236	0.350

The Chinese stock market imposed the "T+1" trading rule on short-selling on August 3, 2015. This table reports the results of regressions (1) and (2) separately for stocks added in the first five batches which are not subject to the "T+1" trading rule on short-selling and stocks added in the sixth batch which are subject to the "T+1" trading rule on short-selling. The variable of interest is Amihud illiquidity ratio, which is the average of stock i's daily Amihud illiquidity ratio over 120 trading days in the pre-event window ($t \in [-120, -1]$ where $T = 0$) or post-event window ($t \in [1, 120]$ where $T = 1$). Stock i's daily Amihud illiquidity ratio is calculated as the absolute value of daily stock return divided by the trading volume in RMB scaled by 10^9. *Post* is an indicator variable set equal to one if the short-selling and margin-buying restrictions are lifted. *Treated* is also an indicator variable set equal to one if stock i is added to the short-selling and margin-buying list. The control variables are the same as in Table 4. The t statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, using standard errors clustered at the batch × stock level.

suggesting that the lift of short-selling and margin-buying constraints has a negative impact on liquidity for the first five batches of subsample stocks. On the other hand, as reported in Panel B of Table 11, the coefficient of $Post * Treated$ is −0.075 with t-stat = −4.53, indicating that the lift of short-selling and margin-buying constraints has a positive impact on liquidity for the 6th batch of subsample stocks. The finding is consistent with our theoretical predictions.

6. Conclusion

We propose a framework based on limit order book to analyze the impact of short-selling and margin-buying on liquidity, where limit orders submitted by investors supply liquidity and market orders consume liquidity. We show that under a dynamic setting with information asymmetry, the adverse selection may lead to deteriorated liquidity as a result of uninformed investors withdrawing their limit orders. As shown in the literature, short-sellers are more likely to be informed. As such, the adverse selection effect is stronger for short-selling. Given that the Chinese stock market has strong information asymmetry and a high proportion of uninformed traders, short-selling and margin-buying may have a negative effect on liquidity. In addition, since the adverse selection is more pronounced for firms with high information asymmetry, we predict that the negative effect of short-selling and margin-buying on liquidity is stronger for stocks with high information asymmetry.

In March 2010, the Chinese stock market launched a pilot program to lift restrictions on short-selling and margin-buying for a designated list of stocks, which is subsequently expanded to 1056 stocks by December 2016. We use this unique event to examine theoretical predictions regarding the impact of short-selling and margin-buying on liquidity. Employing the difference-in-differences methodology, we find that consistent with our theoretical predictions, there is a negative impact of short-selling and margin-buying on liquidity. In addition, the negative effect is stronger for stocks with high information asymmetry, as measured by analysts' earnings forecast dispersion and idiosyncratic volatility. Also consistent with our theoretical predictions, lifting restrictions on short-selling and margin-buying has a negative impact on liquidity for the first five batches of subsample stocks which are not subject to the "T+1" trading rule on short-selling, but a positive effect for the 6th batch of subsample stocks which are subject to the "T+1" trading rule on short-selling.

Our findings show that in contrast to regulators' intention of enhancing market liquidity, short-selling and margin-buying has a significantly negative effect on liquidity in the Chinese stock market. As such, it is important for regulators to evaluate the effect of proposed regulations and policies through rigorous pilot programs. We find that information asymmetry is an important contributor of liquidity deterioration. To mitigate the negative effect on liquidity, regulations and policies should be introduced to require firms to disclosure fundamental information to investors on a timelier basis, improve both internal and external corporate governance, and punish firms that produce fraudulent information, etc.

References

Admati, Anat R., Pfleiderer, Paul, 1988. A theory of intraday patterns: Volume and price variability. Rev. Financ. Stud. 1 (1), 3–40.
Amihud, Yakov, 2002. Illiquidity and stock returns: Cross-section and time-series effects. J. Financial Mark. 5 (1), 31–56.
Amihud, Yakov, Mendelson, Haim, 1988. Liquidity, volatility, and exchange automation. J. Account. Audit. Finance 3 (4), 369–395.
Angrist, D., Krueger, Alan B., 1999. Empirical strategies in labor economics. In: Ashenfelter, Orley, Card, David (Eds.), Handbook of Labor Economics, Vol. III. North-Holland.
Asquith, Paul, Pathak, Parag A., Ritter, Jay R., 2005. Short interest, institutional ownership, and stock returns. J. Financ. Econ. 78 (2), 243–276.
Ausubel, Lawrence M., 1990. Insider trading in a rational expectations economy. Amer. Econ. Rev. 1022–1041.
Bagehot, Walter, 1971. The only game in the town. Financ. Anal. J. 27 (2), 12–14.
Bai, Min, Qin, Yafeng, 2014. Short-sales constraints and liquidity change: Cross-sectional evidence from the Hong Kong market. Pac.-Basin Finance J. 26, 98–122.
Balakrishnan, Karthik, Billings, Mary Brooke, Kelly, Bryan, Ljungqvist, Alexander, 2014. Shaping liquidity: On the causal effects of voluntary disclosure. J. Finance 69, 2237–2278.
Beber, Alessandro, Pagano, Marco, 2013. Short-selling bans around the world: Evidence from the 2007–09 crisis. J. Finance 68 (1), 343–381.
Bhattacharya, Utpal, Spiegel, Matthew, 1991. Insiders, outsiders, and market breakdowns. Rev. Financ. Stud. 4 (2), 255–282.
Black, Fischer, 1986. Noise. J. Finance 41 (3), 528–543.
Boehmer, Ekkehart, Jones, Charles M., Zhang, Xiaoyan, 2013. Shackling short sellers: The 2008 shorting ban. Rev. Financ. Stud. 26 (6), 1363–1400.
Boehmer, Ekkehart, Jones, Charles M., Zhang, Xiaoyan, 2019. Potential pilot problems: Treatment spillovers in financial regulatory experiments. J. Financ. Econ. (forthcoming).
Boehmer, Ekkehart, Wu, Juan Julie, 2013. Short selling and the price discovery process. Rev. Financ. Stud. 26 (2), 287–322.
Bris, Arturo, Goetzmann, William N., Zhu, Ning, 2007. Efficiency and the bear: Short sales and markets around the world. J. Finance 62 (3), 1029–1079.
Brockman, Paul, Chung, Dennis Y., 2003. Investor protection and firm liquidity. J. Finance 58 (2), 921–938.
Chan, Kalok, Menkveld, Albert J., Yang, Zhishu, 2008. Information asymmetry and asset prices: Evidence from the China foreign share discount. J. Finance 63 (1), 159–196.
Chang, Briana, 2018. Adverse selection and liquidity distortion. Rev. Econom. Stud. 85 (1), 275–306.
Chang, Eric C., Luo, Yan, Ren, Jinjuan, 2014. Short-selling, margin-trading, and price efficiency: Evidence from the Chinese market. J. Bank. Financ. 48, 411–424.
Chen, Jun, Kadapakkam, Palani-Rajan, Yang, Ting, 2016. Short selling, margin trading, and the incorporation of new information into prices. Int. Rev. Financ. Anal. 44, 1–17.
Cheng, Louis, Firth, Michael, Leung, T.Y., Rui, Oliver, 2006. The effects of insider trading on liquidity. Pac.-Basin Finance J. 14 (5), 467–483.
Chuang, W.I., Lee, H.C., 2010. The impact of short-sales constraints on liquidity and the liquidity-return relations. Pac.-Basin Finance J. 18 (5), 521–535.
Diamond, Douglas W., Verrecchia, Robert E., 1987. Constraints on short-selling and asset price adjustment to private information. J. Financ. Econ. 18 (2), 277–311.
Diether, Karl B., Lee, Kuan Hui, Werner, Ingrid M., 2009. Short-sale strategies and return predictability. Rev. Financ. Stud. 22 (2), 575–607.
Easley, David, O'Hara, Maureen, 1987. Price, trade size, and information in securities markets. J. Financ. Econ. 19 (1), 69–90.
Fama, Eugene F., French, Kenneth R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56.
Grossman, Sanford J., Stiglitz, Joseph E., 1980. On the impossibility of informationally efficient markets. Amer. Econ. Rev. 70 (3), 393–408.
Guerrieri, Veronica, Shimer, Robert, 2014. Dynamic adverse selection: A theory of illiquidity, fire sales, and flight to quality. Amer. Econ. Rev. 104 (7), 1875–1908.
Hardouvelis, Gikas A., Peristiani, Stavros, 1992. Margin requirements, speculative trading, and stock price fluctuations: The case of Japan. Q. J. Econ. 1333–1370.
Hasbrouck, Joel, 1991. Measuring the information content of stock trades. J. Finance 46 (1), 179–207.
Hirose, Takehide, Kato, Hideaki Kiyoshi, Bremer, Marc, 2009. Can margin traders predict future stock returns in Japan? Pac.-Basin Finance J. 17 (1), 41–57.
Hollifield, Burton, Miller, Robert A., Sandås, Patrik, 2006. Estimating the gains from trade in limit-order markets. J. Finance 61 (6), 2753–2804.
Jiang, George J., Lu, Liangliang, Zhu, Dongming, 2014. The information content of analyst recommendation revisions—evidence from the Chinese stock market. Pac.-Basin Finance J. 29, 1–17.
Jones, Charles M., 2012. Shorting restrictions: Revisiting the 1930s. Financ. Rev. 47 (1), 1–35.
Kahraman, Bige, Tookes, Heather E., 2017. Trader leverage and liquidity. J. Finance 72 (4), 1567–1610.
Kyle, Albert S., 1985. Continuous auctions and insider trading. Econometrica 1315–1335.
Li, Zhisheng, Lin, Bingxuan, Zhang, Ting, Chen, Chen, 2018. Does short selling improve stock price efficiency and liquidity? Evidence from a natural experiment in China. Eur. J. Finance 24 (15), 1350–1368.
Marsh, Ian W., Payne, Richard, 2012. Banning short sales and market quality: The UK's experience. J. Bank. Financ. 36 (7), 1975–1986.
Meng, Qingbin, Li, Ying, Jiang, Xuanyu, Chan, Kam C., 2017. Informed or speculative trading? Evidence from short selling before star and non-star analysts' downgrade announcements in an emerging market. J. Empir. Financ. 42, 240–255.
Saffi, Pedro A.C., Sigurdsson, Kari, 2011. Price efficiency and short selling. Rev. Financ. Stud. 24 (3), 821–852.
Seguin, Paul J., 1990. Stock volatility and margin trading. J. Monetary Econ. 26 (1), 101–121.
Sharif, Saqib, Anderson, Hamish D., Marshall, Ben R., 2014. Against the tide: The commencement of short selling and margin trading in mainland China. Account. Finance 54 (4), 1319–1355.
Tan, Lin, Chiang, Thomas C., Mason, Joseph R., Nelling, Edward, 2008. Herding behavior in Chinese stock markets: An examination of A and B shares. Pac.-Basin Finance J. 16 (1–2), 61–77.
Wan, Xiaoyuan, 2018. Is the idiosyncratic volatility anomaly driven by the MAX or MIN effect? Evidence from the Chinese stock market. Int. Rev. Econ. Finance 53, 1–15.
Wang, Qian, Wong, T.J., Xia, Lijun, 2008. State ownership, the institutional environment, and auditor choice: Evidence from China. J. Account. Econ. 46 (1), 112–134.
Yamamoto, Ryuichi, 2014. An empirical analysis of non-execution and picking-off risks on the Tokyo stock exchange. J. Empir. Financ. 29, 369–383.