Short-selling, margin-trading and price efficiency: Evidence from the Chinese market

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Abstract

China launched a pilot scheme in March 2010 to lift the bans on short-selling and margin-trading for stocks on a designated list. We find that stocks experience negative returns when added to the list. After the bans are lifted, price efficiency increases while stock return volatility decreases. Using panel data, we find higher price efficiency to be associated with intensified short-selling activities. Short-sellers trade to eliminate overpricing by selling stocks with positive contemporaneous returns following a downward trend, while margin-traders tend to buy stocks with negative contemporaneous returns and/or with strong sell-order imbalance. We further show that short-sellers do possess return predictive power, while margin traders do no have such an ability.

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1. Introduction

The impact of short-sale constraints on the capital market is highly controversial. There is intense debate over whether such a constraint induces an upward bias in asset prices, reduces price efficiency, and helps to stabilize the market (Miller, 1977; Diamond and Verrecchia, 1987; Hong and Stein, 2003). Since the U.S. Securities and Exchange Commission temporarily banned short-selling in September 2008, the benefits and costs of this ban have been under intense scrutiny. Discussions concerning margin requirements have attracted the attention of governments, the investing public, and academia since the market crash of October 1987. Margin-traders, as potentially informative speculators, are often blamed for producing excess volatility and destabilizing the market.

Just as the Western developed markets imposed more stringent constraints on short-selling and margin-trading, China launched a long-awaited pilot scheme on March 31, 2010, allowing 90 constituent stocks on a designated list to be sold short and/or purchased on margin. This list was revised twice in 2010, and was then expanded to include 280 constituent stocks and 7 exchange-traded-funds (ETFs) in December 2011. The China Securities Regulatory Committee (CSRC) then announced the successful completion of this pilot scheme and made short-selling and margin-trading routine practice.

This event provides us with a rare opportunity to further investigate the impact of short-selling and margin-trading from several aspects. First, the bans were lifted for a subset of stocks overnight, allowing us to test whether short-sale constraints contribute to share overvaluation by examining the event returns (Chang et al., 2007). Second, we explore the influence of constraints on price efficiency by examining the changes in efficiency and volatility after the bans are lifted Bris et al. (2007). Third, China makes the daily short-selling, margin-trading, and associated covering volume publicly available at the stock level. U.S. researchers, in comparison, usually only observe the monthly short interest. We future examine the relation between efficiency and short-selling/margin-trading activities using panel data (Saffi and Sigurdsson, 2011). Finally, we analyze the relation between trading activity and the past and future stock returns (Diether et al., 2009), which enables us to infer the trading motivations and assess the informativeness of Chinese short-sellers and margin-traders.

Our main results are as follows. First, we examine the stock returns around the event day when a stock is added to the designated list and hence the bans on short-selling and margin-trading are lifted. We find an average abnormal return of -47 bps on the event day, which is significantly negative. The cumulative abnormal returns remain negative for two months following the event. The evidence strongly supports the conjecture that short-sale constraints contribute to overvaluation.

Second, we obtain the weekly returns over the one-year period before and after the event and estimate efficiency measures. The results show that after the bans are lifted, stock return synchronicity, the correlation between stock return and lagged market return, and the variance ratio all reduce significantly in the down markets, yet there's no significant change in these measures in up markets. These pieces of evidence indicate that short-selling and/or margin-trading help to promote price efficiency, especially during market downturns. We then investigate the change in the distributions of weekly returns. After the bans are lifted, we find significantly lower return volatility in both up- and down-market, and less occurrence of extreme stock returns. This contradicts the traditional wisdom that short-sellers and/or margin-traders destabilize the market.

Third, we utilize the panel data on short-selling and margin-trading activities to examine the impact of these activities on price efficiency. We find that short-selling activities are associated with lower down-market R^2 and lower up-market cross-correlation (ρ_+). The covering of short positions is also associated with lower ρ_+. The results imply that the trades of short-sellers help to improve stock price efficiency. Margin traders' contribution to price efficiency, however, is mixed. Whereas margin-trading turnover is negatively associated with ρ_-, ρ_+, and variance ratio, intensified covering of margin position is associated with higher R^2_-, higher R^2_+, and higher ρ_+. Overall, the purchase decision of margin-traders increases price efficiency, whereas their sell decisions reduces efficiency. Besides, we find no evidence that short-selling and/or margin-trading destabilize the market. Intensified covering of short positions and intensified margin-trading turnover are even associated with lower return volatility in both down- and up-market, and these trading activities are associated with a lower fraction of extremely negative returns.

Fourth, we utilize panel data on daily short-selling and margin-trading turnovers at stock level to infer the trading motivations and assess the informativeness of Chinese short-sellers and margin-traders. We find intensified short-selling activities in case of low historical return and high contemporaneous return, indicating "arbitrage" activity against very short-term price rebound in an established downward trend. Intensified short-selling has no observable association with buy-order imbalance, refuting the alternative trading motivation of liquidity provision. Intensified short-selling is accompanied by less sell-order imbalance, suggesting that the trading strategies adopted short-sellers differ a lot from other typical sellers. In addition, intensified short-selling accompanies higher intraday volatility and higher spread, which hints that short-sellers are potentially informative. In brief, we find that short-sellers trade on temporal overpricing in an downward trend. In comparison, margin-trading and associated covering turnover show no identifiable relation with historical returns. We find some obscure evidence that margin-traders buy underpriced stocks but the covering of short positions seems not to be triggered by the reversal of underpricing. We also find evidence that margin-traders provide liquidity to stocks with strong sell-order imbalance, but we find intensified covering of margin positions accompanying both subsided sell- and buy-order imbalance. Further investigation reveals that the sell-order imbalance is rather persistent, and intensified margin-trading tends to be followed by even stronger sell-order imbalance, indicating that the liquidity provision by margin-trader is not profitable.

We then explore whether trades by short-sellers or margin-traders predict future stock returns. Surprisingly, we find that short-sale marginally predicts future returns over up to five trading days, and the covering of short positions has very strong return predictive power even over 20 trading days ahead. Margin-trades, however, have no return predictive power in the observation window. These pieces of evidence suggest that short-sellers possess the ability to identify the temporal price rebound in a downward trend. Margin-traders, as a group, do not have such an ability.

Finally, utilizing intraday transaction data, we categorize trades into small, middle, and large trades according to the average dollar volume. Short-sellers tend to trade in large size, and they trade opposite to middle-size trades. Margin-trades do not fall into any specific size category, but we observe that margin-traders also trade opposite to middle-size trade. This could help to explain why short-sellers and margin-traders do not add to return volatility.

This study contributes to the literature in several aspects. First, we add evidence on the impact of short-selling and margin-trading constraints on the market. Second, to our best knowledge, we are the first to comprehensively examine the impact of short-selling and margin-trading on price efficiency in the Chinese market. Third, we are the first to exploring the trading strategies adopted by Chinese short-sellers and margin-traders. This study potentially helps market participants to understand why, when, and how those special investors trade. The findings in this study provide important policy suggestions to Chinese regulators. The Chinese capital market experienced burgeoning growth in the last two decades, and is now one of the most important financial markets in the world. Chinese regulators try to lift restrictions on the financial market whereas they are still concerned the market stability. Our results suggest that due to the special trading strategy adopted, Chinese short-sellers and/or margin-traders do not destabilize the market. China began the pilot scheme of "refinancing" in August 2012, allowing banks, funds, and insurance company to lend out money to margin-traders, contributing to the soaring volume of margin-trading. "Security refinancing", however, was shelved for stability concerns, greatly limiting the supply of security lending. Our study reveals that short-selling, not margin-trading, promotes price efficiency. In addition, short-sellers, not margin-traders, are the information producers. We thus urge Chinese regulators to speed up the security refinancing scheme to facilitate the further development of the market.

2. Literature review

An investor buys a stock if she has a piece of good news about the underlying firm. If the news is extraordinarily positive with a high precision, then she may build up a leveraged position by borrowing money from the broker (margin-trading) or from other resources. However, she has difficulties in selling the stock short if she has a piece of bad news. Short-selling, the trading activity of selling a borrowed stock without owning it, may be prohibited by law in certain countries, not practiced due to a lack of stock lenders or high security-lending fees, or temporarily infeasible due to the up-tick rule (Bris et al., 2007). The short-sale constraint is arguably more binding than the margin-trading constraint.

2.1. Short-sale constraints and overvaluation

Miller's (1977) seminal model predicts overvaluation associated with the short-sale constraint, as pessimistic investors who do not originally own the stock are prevented from trading. Diamond and Verrecchia (1987), by contrast, predict no overvaluation, as investors have already taken this constraint into account in a rational-expectation framework. Empirical studies largely support the overvaluation view (Autore et al., 2011; Chang et al., 2007; Chen et al., 2002). For example, Chang et al. (2007) take advantage of the institutional setting in Hong Kong, in which only stocks on a pilot list can be sold short. As the list is routinely revised at around quarterly intervals, the authors identify a series of events in which the short-selling ban is lifted or imposed overnight for a subset of stocks. Negative event returns upon the lifting of the short-sale ban strongly supports the overvaluation hypothesis.

2.2. Short-sale constraints, price efficiency, and market stabilization

Another stream of literature studies the impact of the short-sale constraint on price efficiency. Diamond and Verrecchia (1987) predict that the constraint hinders price discovery, especially for negative information. Bris et al. (2007) provide supporting evidence from an international comparison between markets with different institutional settings concerning short-sale constraints. They separately estimate the market model conditional on signed market returns, and use the down- minus up-market R^2 to measure the efficiency loss induced by the short-sale constraint. An alternative efficiency measure is the cross-autocorrelation between stock returns and signed lagged market returns. Based on these two efficiency measures, the authors find that in countries where short-selling is allowed and practiced, prices incorporate negative information more efficiently, supporting Diamond and Verrecchia (1987). In the same spirit, Saffi and Sigurdsson (2011) adopt cross-autocorrelation, a delay measure (Hou and Moskowitz, 2005), and the variance ratio to measure efficiency. They utilize a proprietary data on stock lending and loan fees from 26 countries and find lower efficiency for stocks with more binding short-sale constraint. Consistently, Chen and Rhee (2010) document faster speed of price adjustment for shortable stocks than for non-shortable stocks in Hong Kong by autoregressive (VAR) model.

Since the disastrous 2007-09 crisis and the consequent U.S. short-sale ban in September 2008, the market stabilization function of the short-sale constraint has been even more contentious. According to SEC Chairman Christopher Cox, "the emergency order temporarily banning short selling of financial stocks will restore equilibrium to markets." A similar ban was imposed in France, Belgium, Italy, and Spain in 2011. The stabilization function played by the short-sale constraint, however, is highly controversial. In support of the market stabilization function, Xu (2007) develops a model based on investors who "agree to disagree on the precision of a publicly observed signal", and predicts increasing skewness under the short-sale constraint. In contrast, based on the slow adjustment to negative news, Diamond and Verrecchia (1987) predict more negatively skewed returns under the short-sale constraint. Hong and Stein's (2003) model suggests that due to the short-sale constraint, investors with negative information are sidelined from the market until the market drops when "accumulated hidden (negative) information comes out," which further exacerbates the crash, and thus the returns are more negatively skewed. The empirical results are also mixed. Bris et al. (2007) find that in countries where short-selling is not allowed or practiced, stock returns are less negatively skewed, supporting the stabilization function played by the short-sale constraint. Consistently, Chang et al. (2007) document increased volatility, lower skewness, and more occurrence of extremely negative returns after the short-sale ban is lifted in Hong Kong. In contrast, Saffi and Sigurdsson (2011) find that relaxing the constraint is not associated with increased volatility or more occurrence of negative returns, which does not support the stabilization function. In the same spirit, Boehmer et al. (2013) find that the U.S short-sale ban in September 2008, which was intended to stabilize the turbulent capital markets, failed to support prices. Furthermore, the ban has side-effects by ruining liquidity, slowing down price discovery, and hindering market-making for options.

2.3. Short-selling activity and returns

Despite ample vivid stories about "evil" short-sellers' wrongdoings in the long finance history (Bris et al., 2007), there is still hot debate over the relation between short-selling and past/subsequent returns. Knowledge about short-sellers' trading motivation, strategy, or profitability is also incomplete. Data is the greatest limitation. The commonly used data in U.S. are the monthly short-selling interest (Figlewski, 1981; Karpoff and Lou, 2010, among others). Distinct from the short volume, which is the number of shares sold short during the period, the short interest is the open short positions not covered at the end of the period. Rare intra-day short-selling data were available in U.S. from January 1, 2005 to August 6, 2007, released in the implementation of a regulated SHO pilot scheme (Diether et al., 2009). This precious data set, however, was no longer updated after this scheme ended in 2007. Some researchers are able to obtain proprietary data at the daily frequency or at transaction level, even with some clues to the identity of traders (Boehmer et al., 2008; Cohen et al., 2007, to name a few). Unfortunately, the proprietary data are not publicly available to other researchers.

Diether et al. (2009) investigate the short-term relation between short-selling and returns using regulated SHO data at the transaction level. They find higher short-selling volume following positive returns and before negative returns, and that short-selling positively predicts future returns over the five-trading day horizon. Takahashi (2010) uses Japanese stock lending data and finds that the most heavily shorted stocks underperform the least heavily shorted stocks for up to three months.

The above-mentioned findings raise the question of why short-sellers are able to predict future returns. Diether et al. (2009) propose four alternative explanations. First, short-sellers may possess inside information, especially negative private information. Several studies support this view (Boehmer et al., 2008; Karpoff and Lou, 2010). For example, Karpoff and Lou (2010) document increased short-selling at least one year before a financial misconduct is publicly revealed. Second, short-sellers are likely to be sophisticated investors, who are more capable of identifying overpriced stocks. In support of this view, Boehmer et al. (2008) report that 74% of short-selling orders are executed by institutions, and less than 2% are execute by individual investors. Third, short-sellers may voluntarily provide liquidity by selling short in temporary buying-order imbalance. Once this order imbalance subsides, prices drop back to their fundamental values. Short-sellers then cover the short position at a profit. Fourth, short-sellers may be speculators in voluntarily bearing more risk during high uncertainty. If high uncertainty comes from information asymmetry, more short-selling should coincide with high bid-ask spread, which falls after the information gets public. If high uncertainty comes from divergent opinions, more short-selling should coincide with lower spread because of competitive orders, and the spread widens after opinions converge.

In this study, we utilize the Chinese daily short-selling volume and covering of short positions at stock level to investigate the relation between short-selling activity and returns. As one of the most important developing markets, the Chinese stock market is known for investors' "irrationality". We are thus curious to know the nature of Chinese short-sellers and margin-traders, their trading strategy, whether they are profitable, and whether their trades contribute to market efficiency and/or destabilize the market. [4]

[4] This study is complementary to Sharif et al. (2012a,b). Sharif et al. (2012b) investigate the market reaction to the addition event of the first batch of 90 stocks to the designated list in March 2010 in China. They find negative abnormal returns on both the announcement and implementation days, supporting Miller's (1977) overvaluation hypothesis. They also find lower trading volume following the lifting of the bans, and argue that uninformed investors choose not to participate to avoid trading against informative short-sellers,

2.4. Margin-trading

Margin-trading allows investors to construct a leveraged long position by borrowing capital from registered security companies. Both short-selling and margin-trading were strictly prohibited in China before March 2010. However, the ban on margin-trading was arguably less binding, as investors could easily circumvent this constraint by borrowing from various other resources, and "home-make" leveraged positions even without margin requirements. In addition, if a sufficient number of investors participate in the market, the ban on margin-trading cannot hinder the discovery of positive information.

Traditional wisdom suggests that margin-traders, as potential speculators, trade to destabilize the market. After the market crash in October 1987, regulatory bodies tend to propose more stringent margin requirements to intimidate speculators. Chowdhry and Nanda (1998), however, develop a model that predicts increased market instability brought on by the margin requirements themselves. Since the security purchased on margin serves as the collateral, random fluctuation in stock prices may result in forced liquidation if the margin requirement is rigid enough, leading to excess volatility. Empirical evidence is mixed. Seguin (1990) investigates the inception of the margin-trading for OTC stocks, finding positive event returns, no higher volatility, improved liquidity, and increased price informativeness. In comparison, Hardouvelis and Peristiani (1992) examine stock returns and volatility after margin requirement changes in Japan. They find that after the implementation of higher margin requirement, returns tend to be lower and volatility drops, indicating that a higher margin requirement deters destabilizing speculators and does not incur market instability. Hirose et al. (2009) examine weekly data on Japanese margin-trading and short-selling. Interestingly, they find that although the margin-trading is dominated by retail investors, who are presumably uninformed, their margin-trading positively predicts future returns, especially for small firms.

which leads to reduced market quality. Sharif et al. (2012a) find an increased quoted spread after the lifting of the bans for the 90 stocks, consistent with the non-participation story by uninformed investors.

3. Market reactions

3.1. Institutional background

Short-selling or margin-trading were prohibited in the Chinese security market before the implementation of the pilot scheme in March 2010. Table 1 shows the timeline of this influential reform. On March 31, 2010, the two major exchanges in mainland China allowed "qualified" investors to buy eligible stocks on margin or short-sell those stocks under a pilot scheme. In total, 90 constituent stocks in the SSE 50 Index (on the Shanghai exchange) and SZSE Component Index (on the Shenzhen exchange) on a designated list were eligible for margin-trading and short-selling. This list was revised twice in 2010, with six stocks being deleted and six new stocks being added in July 2010. On December 5, 2011, the exchanges substantially expanded the list to include 278 qualified constituent stocks in the SSE 180 Index and SZSE 100 Index, as well as 7 exchange-traded-funds (ETFs). The CSRC then announced that the pilot scheme would become a routine practice and accordingly revised the detailed implementation rules to stipulate more specific margin requirements.

Stocks and ETFs have to meet several criteria to be eligible for short-selling and margin-trading. According to the implementation rules promulgated by the Shanghai exchange, eligible stocks must satisfy size, liquidity, and volatility requirements.[5] According to the administrative rules promulgated by the CSRC, only "qualified" investors can buy stocks on margin or sell stocks short, and the requirements differ across security companies.[6] It

[5]Source: http://www.sse.com.cn/cs/zhs/xxfw/flgz/rules/sserules/sseruler20111125b.html. First, to be eligible for margin-trading, a firm must have no less than 100 million tradable shares and a public float no smaller than RMB 500 million (US$79.5 million). To be eligible for short-selling, a firm must have no less than 200 million tradable shares and a public float no smaller than RMB 800 million (US$127.3 million). Second, the number of shareholders must be no less than 4,000. Third, in any given day during the past three months on a rolling basis, the daily turnover must be no lower than 15% of index turnover, the daily trading value must be no lower than RMB 50 million (US$7.95 million), its average return must not deviate more than 4% from the index return, and its return volatility must be no higher than five times of the index volatility. The middle exchange rate published by the People's Bank of China was 6.2855 RMB/US$ on December 31, 2012. http://www.chinamoney.com.cn/fe/Channel/17383

[6]Taking the guidance of Haitong Securities as an example, qualified investors must satisfy below requirements. First, an investor must have a trading history longer than one and a half years with that security company (reduced to half a year after December 2011), with capital of no lower than RMB 500,000 (approximately US$ 79,500). The investor must demonstrate the basic knowledge by passing a professional knowledge

seems that, similar to the practice in Japan and Taiwan, short-selling and margin-trading business in China caters retail investors rather than institutions. The up-tick rule is strictly implemented, and naked short-selling is strictly prohibited.

The cost of short-selling and margin-trading is quite high in China. For example, Haitong Securities charge the same fee for security lending and margin-trading for all stocks: 3% above the prime rate for 6-month loans, as the maturity of short- or margin-contract is no longer than 6 months as stipulated by the CSRC. On December 31, 2012, the prime rate for 6-month loans (published by The People's Bank of China) was 5.60%. Thus, Haitong charged 8.60% for margin-trading and stock-lending. Huatai Securities, however, charged 8.60% for margin-trading and 10.60% for security lending. By contrast, D'Avolio (2002) report that the value-weighted loan fee of a sample portfolio is only .25% in U.S., and only 9% of stocks have a loan fee above 1%. Even for stocks with high loan fees, the mean fee is only 4.3%. The limited supply of security lending is also a problem. From March 2010 to August 2012, qualified investors can borrow money or stock only from security companies. Beginning from August 27, 2012, investors can also borrow money from investment banks, funds, and insurance companies through a centralized refinancing company. Security lending, however, is still limited to security companies only.

Margin-trading and short-selling are settled in a shared margin account. In the margin calculation, the collateral value is the discounted value of stocks purchased on margin or sold short, and the discount rate varies with the asset type and across individual stocks. An investor must keep the balance at or above the maintenance level. The position will be forced to close if she fails to meet the margin call within two trading days.

exam and a risk-attitude test. Other qualitative requirements include a good trading record, low bankruptcy risk, and not being a corporate insider, etc. Source: http://www.htsec.com/htsec/Info/1930303.

3.2. Data

We collect information on the designated stock list and revisions from the exchange websites[7]. Data retrieved from the China Stock Market Trading Research (CSMAR) database provided by GuoTaiAn (GTA) Company include (1) daily stock returns, (2) annual financial statements, and (3) high frequency trade and quote data. We obtain daily short-selling volume, margin-trading volume, and respective covering volumes for eligible stocks from WIND.

The sample period spans January 1, 2010 to December 31, 2012. We have 285 stock addition events, 10 ETF addition events, and 7 deletion events in total. Due to the very small sample, we drop the 7 deletion events. Due to the special features of ETFs and the lack of trade and quote data, we drop the 10 addition events for ETFs. We are left with 285 addition events, among which 90 belong to the first batch added to the list on March 31, 2010, and 189 belongs to the second batch added on December 5, 2012. Among these addition events, 4 stocks were added to the list twice, and the time interval is over one year between the first and the second addition.

3.3. Event day returns

Following Chang et al. (2007), we calculate abnormal returns around addition events by the market-model adjusted abnormal returns. An addition event is defined as one in which an individual stock is added to the designated list and thus can be sold short and purchased on margin from the event day, denoted as day 0. We apply the pre-event estimation window of $[-397, -31]$ days before the announcement date, with a minimum of 180 trading days.[8] We estimate the OLS market model by regressing the time series of stock i's daily returns (R_{it}) on the market returns R_{Mt}: $R_{it} = \alpha_i + \beta_i R_{Mt} + \epsilon_{it}$, where the market portfolio is

[7] `http://www.sse.com.cn/sseportal/ps/zhs/sjs/rzrq_home.shtml` and `http://www.szse.cn/main/disclosure/rzrqxx/ywgg/`.

[8] The pre-event window in Chang et al. (2007) is [-280,-31] event days relative to the effective day. In our sample, the interval between the announcement day and effective day on which the scheme was implemented was as long as 47 calendar days (34 trading days) for the first batch. We use the one-year estimation window before announcement day to avoid potential contamination by the announcement events.

the value-weighted return of all stocks traded on the A-share market, using the market capitalization of the public float as the weight. After obtaining the estimated α and β for each firm event, we calculate the market-model adjusted abnormal return $AR_i^m(t)$ for stock i at event day t as $AR_i(t) = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{Mt}$. The cumulative abnormal return during the event window $[t_1, t_2]$ is calculated as $CAR_i[t_1, t_2] = \sum_{t=t_1}^{t_2} AR_i(t)$.

We have 274 firm-events with abnormal returns available on the event days. Table 2 reports the cross-sectional average of the abnormal returns and cumulative abnormal returns by trading days around the addition events. In Panel A, we observe a significantly negative abnormal return of -47 bps on day zero, the event day. Although the abnormal return is significantly positive on day one, its average magnitude is much smaller than that on day zero. In Panel B, $CAR[-5, -1]$, the abnormal returns cumulated during the five trading days before the event, is on average -71 bps, which is significantly negative. As the addition event has been known by the public, selling activities in advance may push this early price drop. $CAR[0, 2]$ is on average -39 bps, which is significantly negative, and $CAR[0, 5]$ is on average -85 bps, which is also significantly negative. The average cumulative abnormal return remains significantly negative up to 40 trading days after the addition event. Figure 1 plots the cross-sectional average of $AR[t]$ and $CAR[-5, t]$ during the window of $[-5, +25]$ trading days relative to the event. We find negative ARs in most days, and an obvious downward trend in CAR throughout the window. This pattern seems persistent and is not followed by evident reversal, consistent with the results in Table 2.[9]

In summary, stock returns upon the implementation of short-selling and margin-trading tend to be negative, consistent with the findings in Sharif et al. (2012b) who examine the returns for a subset of 90 addition events in the first batch on March 31, 2010. The results confirm our conjecture that, although both short-selling and margin-trading were banned before the event, the constraint on short-selling was more binding. Hence, upon the lifting

[9]The initiation of index futures trading was an another influential reform during the period. CSRC announced the plan on February 20, 2010 and the trading of index futures began on April 16, 2010, which is 11 trading days after the initiation of short-selling and margin-trading on March 31, 2010.

of the bans, the overvaluation caused by short-selling bans lead to the documented price drop, supporting Miller (1977).

3.4. Change in price efficiency

Next, we examine whether the short-selling and margin-trading constraints hinder price discovery by examining the change in efficiency around the addition events. We obtain weekly returns during 56 weeks before and after the addition events and apply an pre-event window of $[-56, -5]$ weeks and an post-event window of $[5, 56]$ relative to the event week to estimate efficiency measures. We winsorize stock returns falling out of three standard deviations around the mean. First, following Bris et al. (2007), we estimate the OLS market model separately in the pre-event and post-event estimation windows for each stock to get β and R^2. Higher β indicates greater sensitivity of stock returns to market returns, and lower R^2 indicates higher efficiency as more firm-specific information is incorporate into prices. We also estimate the market model separately conditional on negative (positive) market returns, and denote the beta coefficient as β_- (β_+) and R-square as R^2_- (R^2_+). Second, we estimate the cross-autocorrelation ρ between stock returns and the lagged market returns, conditional on signed lagged market returns. Higher ρ indicates a greater price delay and thus lower efficiency. Third, following Saffi and Sigurdsson (2011), we estimate the variance ratio ($|VR|$) in a rolling way, defined as the absolute value of the variance of monthly returns divided by four times the variance of weekly returns, minus one. Higher $|VR|$ indicates lower efficiency, as the return process deviates more from a random walk.[10] We require a minimum of 36 weeks in each estimation window to calculate the efficiency measures, and a minimum of 16 weeks to calculate signed β, R^2, and ρ. We then perform paired t-test to examine the change in efficiency measures around the addition events.

Panel A of Table 3 shows the comparison results. We find that the down-market β_- increases significantly after the bans are lifted, indicating that stock returns are more sensitive

[10] According to Hou and Moskowitz (2005), the D1 and D2 used in Saffi and Sigurdsson (2011) as efficiency measures are quite noisy at individual stock level. Therefore we abandon this efficiency measure.

to negative information. Consistently, the down-market R^2_- significantly drops after bans are lifted, suggesting more firm-specific information incorporated into stock price and thus greater efficiency. Both $|\rho_-|$ and $|\rho_+|$ drops significantly after the bans are lifted. Specifically, $|\rho_-|$ drops from an average of 23.1% to 14.5%, and this drop is also economically significant. $|VR|$ also drops significantly. All these pieces of evidences reveal greater price efficiency after short-selling and margin-trading are allowed. The asymmetrically improved efficiency in the down-market hints that it is the short-selling constraint that hinders price discovery, and it is short-selling activities that contribute to greater efficiency.

3.5. Change in return distributions

We next utilize the weekly returns during the pre-event and post-event estimation window to investigate the change in return distributions (Chang et al., 2007; Bris et al., 2007). Different from section 3.4, we do not winsorize weekly stock returns here. We obtain volatility, skewness, and kurtosis of weekly returns. Conditional on the sign of weekly stock returns, we calculate the standard deviation of $max(Ret_i, 0)$ as up-side volatility (Vol_+), and the standard deviation of $min(Ret_i, 0)$ as down-side volatility (Vol_-). $Extreme_-$ ($Extreme_+$) is the occurrence of extremely negative (positive) returns, calculated as the fraction of weeks in which returns are two standard deviations below (above) the average for each stock. If bans on short-selling and margin-trading stabilize the market, and/or the trades by short-sellers or margin-traders destabilize the market, we expect to observe higher volatility, lower skewness, and higher occurrence of extreme returns after the bans are lifted.

Panel B of Table 3 reports the comparison results. Contrary to the stabilization role played by constraints, however, we observe lower down-side and up-side volatility, higher skewness, and lower occurrence of both extremely positive and negative returns. Such results show that the trades by Chinese short-seller and margin-traders do not destabilize the market. This evidence somehow contradicts the U.S. evidence (Bris et al., 2007) and Hong Kong evidence (Chang et al., 2007), but is consistent with the international evidence from Saffi and Sigurdsson (2011). We will discuss the potential reasons in the cross-sectional tests in section 5.2.

4. Short-selling and margin-trading activities

As we discuss in section 2.3, China makes the panel data on daily short-selling and margin-trading volume publicly available, which is a precious dataset allowing us to do many cross-sectional test. In this section, we further investigate the impact of short-selling and margin-trading constraints by examining the relation between trading activities and efficiency measures.

4.1. Summary statistics

We report the summary statistics for short-selling, margin-trading, and covering activities in Table 4. Panel A shows the statistics for short-selling and related covering activities, and Panel B shows the statistics for margin-trading and related covering activities. The two panels clearly show that short-selling and margin-trading are becoming more popular. For example, the average daily short volume as a percentage of daily trading volume is only .01% in 2010, and this ratio grows to .73% in 2012. Margin-trading is more popular than short-selling. The average daily margin volume as a percentage of trading volume is .78% in 2010, and this ratio grows to 5.15% in 2012. Several facts may contribute to this trend. First, the security lending fee for short-selling is no lower than the interest charge for margin-trading. Second, the supply of security lending in short-selling is relatively more limited than supply of capital in margin-trading, especially after the refinancing mechanism implemented in August 2012. Third, the up-tick rule adds to the difficulties of short-selling. Fourth, due to the unlimited potential losses, short-selling itself is riskier than margin-trading. Finally, as Chinese investors are new to the short-selling mechanism, it is not surprising that many of them choose to steer clear of short-selling. All these facts suggest that the barriers to entry for short-selling are higher than those for margin-trading.

4.2. Impact of trading activities on efficiency and return distribution

Following Saffi and Sigurdsson (2011), we estimate the yearly efficiency measures from weekly returns for each stock. Then we obtain the yearly average of daily short-selling or margin-trading turnover and associated covering for each stock. Turnovers are defined as the daily short/margin/covering volume scaled by daily total trading volume. After aggregated to year level, covering of short (margin) turnover is extremely highly correlated with short (margin) turnover itself. To deal with multicollinearity, we regress yearly covering of short (margin) turnover on short (margin) turnover and take the residual as orthogonalized covering turnover. Utilizing this panel data, we regress efficiency and volatility measures on trading activities to investigate the impact of short-selling and margin-trading activities. Following Saffi and Sigurdsson (2011), we also control for log firm size, yearly turnover ratio, dummy variables for dual-listed A-H stocks and A-B stocks. The coefficients on those control variables are not reported for brevity. Following (Thompson, 2011), we use the standard errors clustered by stock and year to deal with potential serial correlation and cross correlation.

Table 5 shows the regression results. In panel A we find that intensified short-selling activity is associated with lower R^2 conditional on negative market returns, indicating more firm-specific bad news incorporated into stock prices accompanying more short-selling. Both intensified short-selling and covering activities are associated with lower cross-correlation. These two pieces of evidence suggest greater price efficiency associated with intensified short-selling activities. It is confusing why short-selling and associated covering activities are associated with reduced cross-correlation conditional on positive lagged market return. In the section 5.1, we will explore the trading strategies deployed by short-sellers in greater details. The contribution by margin-trading activities, however, is mixed. We discover that intensified margin-trading activities are associated with higher price efficiency, indicated by lower cross-correlation conditional on both negative and positive lagged market returns and lower variance ratio. Intensified covering activities of short positions, however, are associated with lower efficiency, indicated by significantly higher R^2 in both up- and down market, and marginally higher cross-correlation in the up-market.

The impact on return distribution is straightforward. Panel B of Table 3 clearly shows that intensified buying activities, induced by both covering of short positions and margin-trading, are associated with lower up- and down-side volatility and less occurrence of extremely negative returns. Even the selling activity induced by covering of margin positions is associated with less occurrence of extremely negative returns. Such evidence contradicts the conventional wisdoms that short-sellers and margin-traders speculate on their private information and destabilize the market.

5. Short-selling, margin-trading, past return, and future returns

5.1. Trading strategies adopted by short-sellers

Next, by utilizing the daily trading activities by short-sellers and margin-traders, we try to infer the trading strategies deployed by Chinese traders.

Diether et al. (2009) document that U.S. short-sellers are able to identify overpricing by short-selling stocks with high historical return and high contemporaneous return. Accordingly, we regress the stock-level short-selling turnover ($Short_t$) on the cumulative stock return over the past five trading days ($r_{-5,-1}$) and the contemporaneous return (r_t). If Chinese short-sellers adopt the same tradings strategy as their U.S. counterpart, the coefficient on $r_{-5,-1}$ and r_t are expected to be positive. As the result of the Augmented Dickey-Fuller test rejects the existence of a unit root in the series of daily short turnover, we control for $Short_{t-1}$ in the panel regressions. We use the standard errors clustered by stock and date.

We report the regression results in column (1) of Table 6. In sharp contrast to the findings by Diether et al. (2009), we find a significantly negative coefficient on $r_{-5,-1}$. The coefficient on r_t, however, is significantly positive, and the magnitude of the coefficient on r_t is greater than that on $r_{-5,-1}$, consistent with Diether et al. (2009). These coefficients imply that a -10% return in the past 5 days increases the short-selling turnover by .03%, whereas a 10% contemporaneous return increases the short-selling turnover by .09%. In comparison, the average daily short turnover in 2012 is just .73% (Table 4). These results suggest that Chinese short-sellers also arbitrage against overpricing. Such overpricing, however, is a very temporal price rebound after low returns in the past week. They seem to believe in the persistence of the trend. The positive return following a downward trend, therefore, is believed to be temporal and will reverse very soon. The causal relation between r_t and $short_t$ cannot be argued in the other way, as short-selling leads to negative price impact and hence predicts a negative coefficient on r_t.

An alternative trading motivation is that traders voluntarily provide liquidity by short-selling in temporal buy-order imbalance and recover the position in reversed buy-imbalance. *Oimb*, the order imbalance, is the difference between daily buy volume and sell volume, scaled by daily total volume. Sell-order imbalance $Oimb^-$(buy-order imbalance $Oimb^+$) is $|Oimb|$ if $Oimb < 0(> 0)$ and zero otherwise. We follow the buy-sell indicator provided by GTA. It is noted that the short-selling and margin-trading volume are included in the transaction data in calculating the buy/sell imbalance. Table 6 shows no evidence supporting liquidity provision, as short-selling turnover has no observable relation with the buy-order imbalance. Short-selling turnover is negatively associated with the sell-order imbalance. Taking into consideration that the short-selling is included in sell volume, it seems that the trading pattern by short-sellers are quite different from other typical sellers.

To examine the opportunistic risk-bearing hypothesis, we use daily volatility (σ), defined as day high minus day low, scaled by day high. To discriminate between the information asymmetry and divergence opinions, we use *Spread*, the volume-weighted average of the effective spreads on a day. Column (1) of Table 6 show that intensified short-selling is accompanied by higher intraday volatility and higher bid-ask spread, indicating risk-bearing in increased uncertainty induced by information asymmetry. Such result hints that short-sellers are likely to be informed traders.

Other control variables unreported for brevity include the lagged dependent variable, the average share turnover in the past five trading days, the average sell- and buy-order imbalance in the past five trading days, the average σ in the past five trading days, the log firm size, and book-to-market ratio.

Column (2) of Table 6 reports the regression results with $Cover^{Short}$ as the dependent variable. The negative coefficient on $r_{-5,-1}$ suggests that the duration of this short position is quite likely to be short. The negative coefficient on r_t suggests that short-sellers cover the short positions after the "temporal" overpricing is reversed. The covering behavioral also suggests a contrarian view. To maximize the profit of the short positions, short-sellers hold the short position following a downward trend until the overturn and the upward trend begins. Next, we observe negative relation between covering of short positions and the buy and sell-order imbalance. It seems that the buy decisions by short-sellers where made on a day when the buy-sell pressure is relatively balanced. The buy decisions are also accompanied by increased volatility induced by increased information asymmetry, suggesting that the buy decisions by short-sellers are likely to be informed.

To conclude, Chinese short-sellers they trade on very short-term overpricing by short-selling in response to a positive return following negative historical returns, and cover the short positions after overpricing is reversed. They seem to hold the belief that the past trend will continue, and the rebound following a downward trend shall be temporal and reverse very soon. Short-sellers are momentum trader when establishing their short positions and contrarian when covering the short positions. Short-sellers do not provide liquidity in buy-order imbalance. Intensified short-selling is accompanied by higher uncertainty and higher information asymmetry, suggesting short-sellers to be informative traders. Overall,

5.2. Trading strategies adopted by margin-traders

Following the methodology used in the previous section, we propose below motivations for margin-trading. First, margin-traders possess private positive information. Second, they have better skill to identify undervalued stocks. Third, they provide liquidity by buying stock on margin when there is a temporary sell-order imbalance. Fourth, they speculate in increased uncertainty. We examine these trading motivations using panel regressions by regressing daily margin-trading turnover on historical and contemporaneous returns.

The regression results are reported in column (3) of Table 6. First, the coefficient on $r_{-5,-1}$ is indistinguishable from zero in column (3), suggesting no relation between margin-trading and historical returns. The coefficient on r_t, however, is significantly negative, suggesting a contrarian strategy adopted by margin-traders by buying underperformed stock. This shows that margin-traders do not trade on momentum, but on temporal underpricing. Interestingly, we find intensified margin-trading in strong sell-order imbalance and attenuated margin-trading in strong buy-order imbalance. This is consistent with liquidity provision, and it also suggests that margin-traders take opposite position to other investor groups. Therefore, it is not surprising to observe a negative coefficient on σ_t, indicating reduced volatility accompanying intensified margin-trading activities, consistent with the findings in Table 5. Besides, intensified margin-trading is associated with greater spread, suggesting more informative trades by either margin-trader or their opposite sellers.

In column (4), we find no relation between covering of margin-positions and historical returns either, and a marginally negative relation between covering of margin positions and r_t. This is quite surprising. If margin-traders buy to arbitrage very short-term underpricing, we shall observe intensified covering of margin positions following positive returns, which is not found. Hence, we reject the underpricing hypothesis as a potential trading motivation for margin-traders. If margin-traders buy to provide liquidity in sell-order imbalance, we shall observe intensified covering of margin positions accompanying subsided sell-order imbalance or stronger buy-order imbalance, and thus expect a negative coefficient on $oimb^-$ and a positive coefficient on $oimb^+$. However, we observe significantly negative coefficients on both $oimb^+$ and $oimb^-$. It seems that, like the covering of short positions, the covering of margin positions intensifies on a day with balanced buy-sell pressure. Hence, the support to the liquidity provision hypothesis is quite obscure.

To sum up, Chinese margin-traders do not trade on momentum or on underpricing.

They buy opposite to strong selling pressure, but we find no sufficient evidence that they intentionally provide liquidity. By trading against other investors, intensified margin-trading is associated with lower volatility.

5.3. Can short-sellers or margin-traders predict future returns?

In the previous two sections, we show that short-sellers believe in the trend and "arbitrage" away very short-term overpricing, and cover the short positions in response to negative returns after overpricing is reversed. The trading pattern by margin-traders, however, show no observation relation with historical returns. Although we seem to observe margin-trades in response to very short-term underpricing or liquidity provision, the covering pattern is inconsistent with either underpricing or liquidity provision hypotheses. If Chinese short-sellers or margin-traders possess superior information or skills, their trades should predict future returns. In other words, intensified short-selling should negatively predict future returns and intensified margin-trading should positively predict future returns. Intensified covering of short (margin) positions indicates a higher likelihood that the downward (upward) trend is over and an upward (downward) trend is to begin and thus future returns should be higher (lower). In this section, we examine whether the trades of short-sellers or margin-traders predict future returns. Although we cannot match covering activity to their respective original positions, we can still make a reasonable conjecture about whether trades are profitable within a certain investment horizon.

Following Diether et al. (2009), we examine the return predictability using panel data regression, with future abnormal returns as the dependent variable. We skip for one day to eliminate the impact of bid-ask bounce, if there is any. The abnormal return is the daily raw return minus the expected return from the market model. We estimate the OLS market model with a rolling window of $[-396, -31]$ calendar days with a minimum of 180 trading days. The key explanatory variables are the daily short turnover ($Short_t$), the margin turnover ($Margin_t$), covering of the short turnover ($Cover_t^{Short}$), and covering of the margin turnover ($Cover_t^{Margin}$). Control variables include the cumulative stock return in the past five trading days, the contemporaneous stock return, the volume-weighted effective spread, the contemporaneous buy/sell-order imbalance, and the intraday volatility. Some other control variables unreported for brevity include the average share turnover in the past five trading days, log firm size, and book-to-market ratio.

The regression results are reported in Table 7. On one-day forecast horizon, we find that intensified short-selling on day t is associated with marginally lower future returns on day $t+2$, and that intensified covering of short positions on day t is associated with significantly higher future returns on day $t+2$. Intensified margin-trading and covering turnover, however, do not have observable predictive power for future returns. It seems that short-sellers, on aggregate, are informative; margin-trader, however, are not. The predictive power of short-selling activity remains in one-week horizon, whereas the predictive power of margin-trading remains very strong even in 20 trading days. Such evidence echos what we found in previous. As the trades by short-sellers are informative, short-selling activities increase the price efficiency (Tables 3 and 5). As margin-traders trade opposite to other potentially informative sellers (Table 6), although they work to stabilize the market, their trades do not contribute to price efficiency (Tables 3 and 5).

In the control variables part, $r_{-5,-1}$ has a negative coefficient, and the explanatory power of this historical return turns stronger in longer period. This evidence indicate that returns in China tend to follow a short-term reversal. Higher *spread* predicts higher future return. More buying pressure, however, predicts lower future return. Higher volatility and turnover ratio predicts higher future return.

6. Further discussions

6.1. Technical indicators

Diether et al. (2009) find intensified short-selling activities following positive returns, especially when the stock becomes a cross-sectional "winner". Technical analysis is one of the most popular "skills" adopted by both retail investors and institutions to identify a "trend" and design trading strategies in China. In this section, we explore whether technical indicators explain or predict the short-selling and margin-trading activities.

Similar to Diether et al. (2009), we use two cross-sectional technical indicators. On each day we rank all shortable stocks by $r_{-5,-1}$, and the dummy $Winner_{-5,-1}$ ($Loser_{-5,-1}$) equals one for stocks ranked in the top (bottom) quintile and zero otherwise. Similarly, we rank stocks by r_t and define $Winner_t$ and $Loser_t$.

Following Brock et al. (1992), we identify four time-series technical indicators according to the moving average (MA) rule and the trading range breakout (TRB) rule. We assign a dummy $Down^{MA}_{-1}$ that equals one if the stock price on day $t-1$ drops and crosses over the past 20-trading day's moving average, which indicates an established downward trend and is thus a sell signal, and zero otherwise. Similarly, Up^{MA}_{-1} equals one if the price on day $t-1$ rises and crosses over the 20-day moving average, which is a buy signal. We assign a dummy $Down^{TRB}_{-1}$ (Up^{TRB}_{-1}) that equals one if the stock price on day $t-1$ drops (rises) and penetrates the past 250-trading days' minimum (maximum) and zero otherwise. Brock et al. (1992) argue that TRB indicates a long-term trend being established and thus $Down^{TRB}$ is a strong sell signal and Up^{TRB} is a strong buy signal. Similarly, we define these four indicators based on r_t. In sum, we use two MA indicators, two TRB indicators, and *Loser* and *Winner* dummies to predict/explain short-seller or margin-trader's trading activity. Control variables unreported for brevity include the lagged dependent variable, the contemporaneous bid-ask spread, sell/buy order imbalance, σ, and the historical average turnover ratio, sell/buy order imbalance, σ in the past five trading days, log firm size, and book-to-market ratio.

The regression results are reported in Table 8. In Panel A, the explanatory variables are technical indicators based on historical returns. In Panel B, the explanatory variables are technical indicators based on r_t. As shown in column (1) of Panel A, short-sellers favor stocks that are past losers, with historical prices drop below the short-term moving average, and/or penetrate the 1-year minimum. In a word, they are searching for stocks with well established downward trend. Besides, they avoid trading stocks with established upward trend, either in the short-term or long-term. Column (1) of Panel B shows that short sellers search for very short-term overpricing in an established downward trend by short-selling stocks that are currently winners but with prices drop and penetrate 1-year minimum. Such evidence suggests that technical analysis is indeed a helpful tool to predict and explain short-sellers trading strategies.

In column (2), we regress covering of short positions on technical indicators. Panel A shows that the coefficients on technical indicators are largely similar to those in column (1), except for r_t, indicating that the decision to recover the short positions is triggered by the contemporaneous return. In panel B, we observe that covering of short positions happens for stocks that are either concurrent winner or losers. The positive coefficient on $loser_t$ is consistent with the results in Table 6, suggesting covering of short positions after overpricing disappears. The positive coefficient on $winner_t$, however, might suggest closure of short positions to stop loss for cross-sectional winners. Negative coefficients on up_t^{MA} and up_t^{TRB}, however, indicate that losses incurred in short positions do not result in forced closures of short positions.

The margin-traders rely less on technical analysis. Consistent with what we find in Table 6, they do not trade on momentum. From column (3) of panel A, however, we can tell that margin-traders avoid trading stocks with prices breaking out the 1-year minimum. Panel B shows that margin-traders favor concurrent losers, which is consistent with the very short-term contrarian strategy observed in Table 6. Consistently, they avoid trading stocks that are concurrent winner, and/or stocks with short-term upward trend or long-term downward trend. And, they do not cover margin positions for contemporaneous winners or lowers. Combined with the positive coefficient on r_t in column (4) of panel A, we can safely reject the underpricing hypothesis as a trading motivation.

To sum up, we find evidence that Chinese short-sellers use technical analysis. Specifically, they search for stocks in an established downward trend but show a contemporary positive return. They appear to follow both cross-sectional and time-series technical indicators to identify trends. Margin-traders, however, do not rely on technical analysis so much as short-sellers. Margin-traders do not identify trend. Instead, they try to capture very short-term underpricing, and we find no evidence that they successfully do so at a profit.

6.2. The identity of Chinese short-sellers and margin-traders

Who are those short-sellers and margin-traders? Are they retail investors, wealthy individuals, or institutions? Based on transaction data, we form our best conjecture concerning their identity.

We collect 5-second transaction data from GTA. For records with non-zero trading volume, we obtain the average dollar size by dividing the trading volume by the number of trades in this 5-second. Since the number of trades data are only available for stocks traded on the Shenzhen exchange, the results reported in this subsection only cover a subsample of all shortable/marginable stocks. Following Ng and Wu (2007), we label trades with an average dollar size below RMB 10,000 as small orders, trades with an average dollar size greater than or equal to RMB 10,000 and below RMB 50,000 as median orders, and trades with an average dollar size greater than or equal to RMB 50,000 as large orders. It is highly likely that small trades are submitted by retail investors, whereas large trades are submitted by institutions or wealthy individuals. In addition, we follow the buy/sell indicator provided by GTA to categorize trades to buyer- or seller-initiated.

Panel A of Table 9 reports the summary statistics of trades. About 65% trades are of a middle size, and these trades contribute to about 65% of trade value. Although small buy and sell orders contribute to about 30% of trades, the value of trades is no more than 10%. In contrast, although large buy and sell orders contribute to only 6% of trades, the value of these trades is about 27% of trade value. Panel B shows the relation between excess buy/sell and past/conterminous returns. We follow Ng and Wu (2007) to define daily excess large buy as *max[(large buy - large sell)/(large buy + large sell),0]*, adjusted by the average excess large buy of all available stocks on day t. We define excess buy/sell from other investor groups in a similar way. In column (1) of panel B, we regress excess large buy on $r_{-5,-1}$ and r_t. It is obvious that large buy-order increases as the historical return and contemporaneous return are lower, suggesting a contrarian strategy adopted by traders submitting large orders, who are likely to be institutions or wealthy individuals. Column (2) shows no observable pattern between the sell decision and returns for investors who submit large orders. Column (3) reveals that either investors submitting middle-size orders trade on positive returns, or their trades result in a contemporary positive return. Columns (4) and (6) suggest that small and middle-size sell orders are contrarian traders: they sell stocks with positive historical returns. By comparing these results to Table 6, it seems that the trading strategy deployed by Chinese short-sellers or margin-traders are quite unique, since their trading pattens are not consistent with any typical investor groups identified here.

In panel C, we regress trading activities by short-sellers or margin-traders on the buy or sell from typical investors groups to examine any similarity between them. In the first row of panel C, we regress the daily short turnover on excess large/small buy/sell. Note that the short volume is included in the calculation of excess sell, and higher short turnover leads to greater selling pressure by construction. The positive association between short turnover and large sell-orders indicates that short-sellers are more likely to submit large sell-order. However, they trade contrarian to investors who submit middle-size orders. The covering of short positions has a very noisy pattern, and it increases in large sell and decreases in middle-size buy and sell-orders. We do not find margin-trader trade in a way consistent with any typical investor groups. However, margin-trader are obviously opposite to investors who submit middle-size orders, confirming the lower volatility associated with intensified margin-trading found in the previous sections.

Finally, we regress future returns on trades from different investor groups to examine whether the buy/sell by large/middle/small investors contain private information. Panel D of table 9 shows that on one-day horizon, middle-size sell-orders mistakenly predict future returns whereas small-size sell-orders correctly predict future returns. Over one-week horizon, large-size and middle-size sell orders mistakenly predict future returns. None of them are able to have any predictive power for returns longer than one-week. In comparison, the trading behaviors by short-sellers correct predict future market returns, even in 20-day horizon.

To sum up, it seems that Chinese short-sellers and margin-traders are quite special investor groups. Their trading patterns do not replicate the trading strategy by any typical large/middle/small investor groups. It seems more likely that they trade opposite to the dominating power in the market who submit middle-size bids, leading to lower volatility as we observed in Tables 3 and 5. On ex-post basis, investors submitting middle-size bids are not able to correctly predict future returns; short-sellers, however, can.

6.3. Portfolio insurance

The increase in short-selling is likely to be driven by increased scale of principal-guaranteed fund. We obtain the share of funds categorized as "principal-guaranteed" from WIND. In Figure 2, we plot the aggregated fund share in billion RMB by month in gray bars. In addition, we plot the aggregated monthly short-selling volume in million RMB in solid line, and the aggregated margin-trading volume by 10 million RMB in dashed line. It is quite obvious that the margin-trading volume show a clear upward trend, whereas the increase in short-selling is relatively depressed, especially in 2012. The policy support tilted toward margin-trading in the refinancing pilot scheme beginning from August 2012 partially contributes to such a trend. Unreported results indicate that the correlation between short volume and fund shares is as high as 90%, and the correlation between margin volume and the share of principal-guaranteed fund is only 45%. Hence, it is likely that one potential motivation for short-selling is replicate the portfolio insurance. If funds are rebalanced on daily basis or on program-trading basis, managers adjust stock positions in response to contemporaneous stock return by buying winners and selling losers. This is inconsistent with the evidence we observed in Table 6. Therefore, although portfolio insurance exercised by guaranteed fund is a potential motivation for short-selling, it is not a dominating one.

6.4. Learning curve

An emerging market arguably has abundant profitable opportunities at the initiation of an influential reform. Through a learning process, others investors can mimic some of the trading strategies adopted by short-sellers and margin-traders. Hence, if a substantial proportion of short-seller's profit come from skills that can be learned and mimicked, we expect to observe less predicative power by short-sellers in the more recent period. If short-seller's profit comes from very sophisticated skills or private information produced with high cost, we will not see too much changes in the short-seller's predicative power during this learning process.

We perform subsample analysis of return predictability and report the results in Table 10. Comparisons between panels A and B reveal that the predictive power by covering of short positions remain quite strong even in the recent subsample period. Actually, when we compare Table 10 to Table 7, the predicative power by short-selling is more pronounced with the recent subsample, suggesting that the trading strategy by short-sellers are not easy to mimic. Short-seller's profits are likely driven by very sophisticated skills or private information.

6.5. Margin-traders: profitable liquidity provision?

As revealed in Table 6, margin-trades buy in case of strong sell-order imbalance and cover the margin positions in subsided sell-order imbalance, although they also cover the margin positions in subsided buy-order imbalance. We next explore whether this liquidity provision by margin-traders in sell-order imbalance is profitable. In unreported results, we regress the buy-/sell-order imbalance on the margin-trading turnover and covering turnover on day $t-1$, controlling for the average buy-/sell-order imbalance in the previous five trading days. We find that intensified margin-trading activities tend to be followed by even stronger sell-order imbalance and weaker buy-order imbalance. Such results remain robust after we change regressors to the average margin-trading turnover and covering turnover in the past five trading days. In addition, the order imbalance is quite persistent; the correlation between order imbalance on day t and the average order imbalance in the previous five days is 0.20, significantly positive. These results suggest that if margin-traders buy to provide liquidity, this strategy is unprofitable as the sell-order imbalance does not fade out immediately.

7. Conclusion

In this study, we examine the impact of short-selling and margin-trading in the Chinese market from various perspectives. First, we examine the impact of bans on short-selling and margin-trading and find negative event returns when the bans are lifted. Second, we find higher price efficiency and lower volatility after the bans are lifted. Third, we find that intensified short-selling is associated with higher efficiency, whereas both intensified short-selling and margin-trading are associated with lower volatility. Fourth, we find intensified short-selling in response to higher contemporaneous return and following lower historical return, suggesting that they trade against temporal overpricing in an established downward trend. Return predictability tests reveal that the trades by short-sellers are able to predict future returns. Our results suggest that short-sellers are informed traders. Furthermore, short-sellers and margin-traders are not market destabilizers. By trading opposite to other investors groups, short-selling and margin-trading effectively reduces return volatility.

References

Autore, D. M., Billingsley, R. S., Kovacs, T., 2011. The 2008 short sale ban: Liquidity, dispersion of opinion, and the cross-section of returns of US financial stocks. Journal of Banking and Finance 35 (9), 2252–2266.

Boehmer, E., Jones, C. M., Zhang, X., 2008. Which shorts are informed? The Journal of Finance 63 (2), 491–527.

Boehmer, E., Jones, C. M., Zhang, X., 2013. Shackling short sellers: The 2008 shorting ban. Review of Financial Studies 26 (6), 1363–1400.

Bris, A., Goetzmann, W. N., Zhu, N., 2007. Efficiency and the bear: Short sales and markets around the world. The Journal of Finance 62 (3), 1029–1079.

Brock, W., Lakonishok, J., LeBaron, B., 1992. Simple technical trading rules and the stochastic properties of stock returns. The Journal of Finance 47 (5), 1731–1764.

Chang, E. C., Cheng, J. W., Yu, Y., 2007. Short-sales constraints and price discovery: Evidence from the Hong Kong market. The Journal of Finance 62 (5), 2097–2121.

Chen, C. X., Rhee, S. G., 2010. Short sales and speed of price adjustment: Evidence from the Hong Kong stock market. Journal of Banking and Finance 34 (2), 471 – 483.

Chen, J., Hong, H., Stein, J. C., 2002. Breadth of ownership and stock returns. Journal of Financial Economics 66 (2-3), 171–205.

Chowdhry, B., Nanda, V., 1998. Leverage and market stability: The role of margin rules and price limits. The Journal of Business 71 (2), 179–210.

Cohen, L., Diether, K. B., Malloy, C. J., 2007. Supply and demand shifts in the shorting market. The Journal of Finance 62 (5), 2061–2096.

D'Avolio, G., 2002. The market for borrowing stock. Journal of Financial Economics 66 (2-3), 271–306.

Diamond, D. W., Verrecchia, R. E., 1987. Constraints on short-selling and asset price adjustment to private information. Journal of Financial Economics 18 (2), 277–311.

Diether, K. B., Lee, K., Werner, I. M., 2009. Short-sale strategies and return predictability. Review of Financial Studies 22 (2), 575–607.

Figlewski, S., 1981. The informational effects of restrictions on short sales: Some empirical evidence. The Journal of Financial and Quantitative Analysis 16 (4), 463–476.

Hardouvelis, G. A., Peristiani, S., 1992. Margin requirements, speculative trading, and stock price fluctuations: The case of Japan. The Quarterly Journal of Economics 107 (4), 1333–1370.

Hirose, T., Kato, H. K., Bremer, M., 2009. Can margin traders predict future stock returns in Japan? Pacific-Basin Finance Journal 17 (1), 41–57.

Hong, H., Stein, J. C., 2003. Differences of opinion, short-sales constraints, and market crashes. Review of Financial Studies 16 (2), 487–525.

Hou, K., Moskowitz, T. J., 2005. Market frictions, price delay, and the cross-section of expected returns. Review of Financial Studies 18 (3), 981–1020.

Karpoff, J. M., Lou, X., 2010. Short sellers and financial misconduct. The Journal of Finance 65 (5), 1879–1913.

Miller, E. M., 1977. Risk, uncertainty, and divergence of opinion. The Journal of Finance 32 (4), 1151–1168.

Ng, L., Wu, F., 2007. The trading behavior of institutions and individuals in Chinese equity markets. Journal of Banking and Finance 31 (9), 2695–2710.

Saffi, P. A. C., Sigurdsson, K., 2011. Price efficiency and short selling. Review of Financial Studies 24 (3), 821–852.

Seguin, P. J., 1990. Stock volatility and margin trading. Journal of Monetary Economics 26 (1), 101–121.

Sharif, S., Anderson, H. D., Marshall, B. R., 2012a. Against the tide: The commencement of short selling and margin trading in mainland China. Unpublished working paper, Massey University.

Sharif, S., Anderson, H. D., Marshall, B. R., 2012b. The announcement and implementation reaction to China's margin trading and short selling pilot programme. Unpublished working paper, Massey University.

Takahashi, H., 2010. Short-sale inflow and stock returns: Evidence from Japan. Journal of Banking and Finance 34 (10), 2403–2412.

Thompson, S. B., 2011. Simple formulas for standard errors that cluster by both firm and time.

Journal of Financial Economics 99 (1), 1–10.

Xu, J., 2007. Price convexity and skewness. The Journal of Finance 62 (5), 2521–2552.

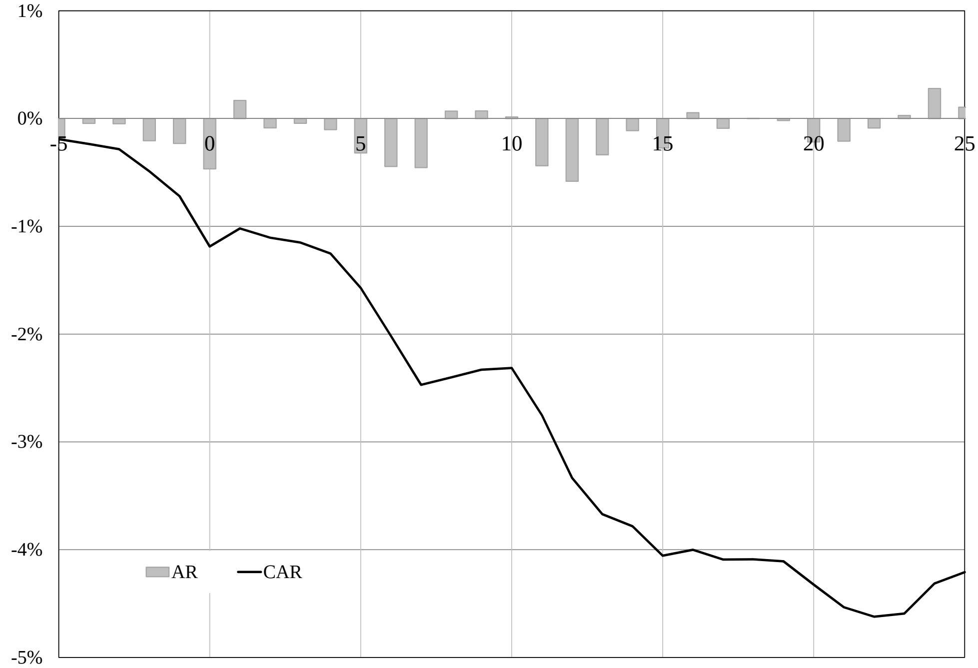

Figure 1: **Abnormal returns and cumulative abnormal returns around additions** This figure plots the abnormal returns and cumulative abnormal returns around addition events. The horizontal axis shows the event time in trading days relative to the addition event. An addition event is defined as one in which an individual stock is added to the designated list and therefore can be sold short or purchased on margin from the event day. The vertical axis shows the daily abnormal returns in bars and the cumulative abnormal returns in lines. The abnormal return is the daily return minus the expected returns by the OLS market model. To estimate the market model, we apply an estimation window of $[-396, -31]$ in calendar days relative to the announcement day, with a minimum length of 180 trading days.

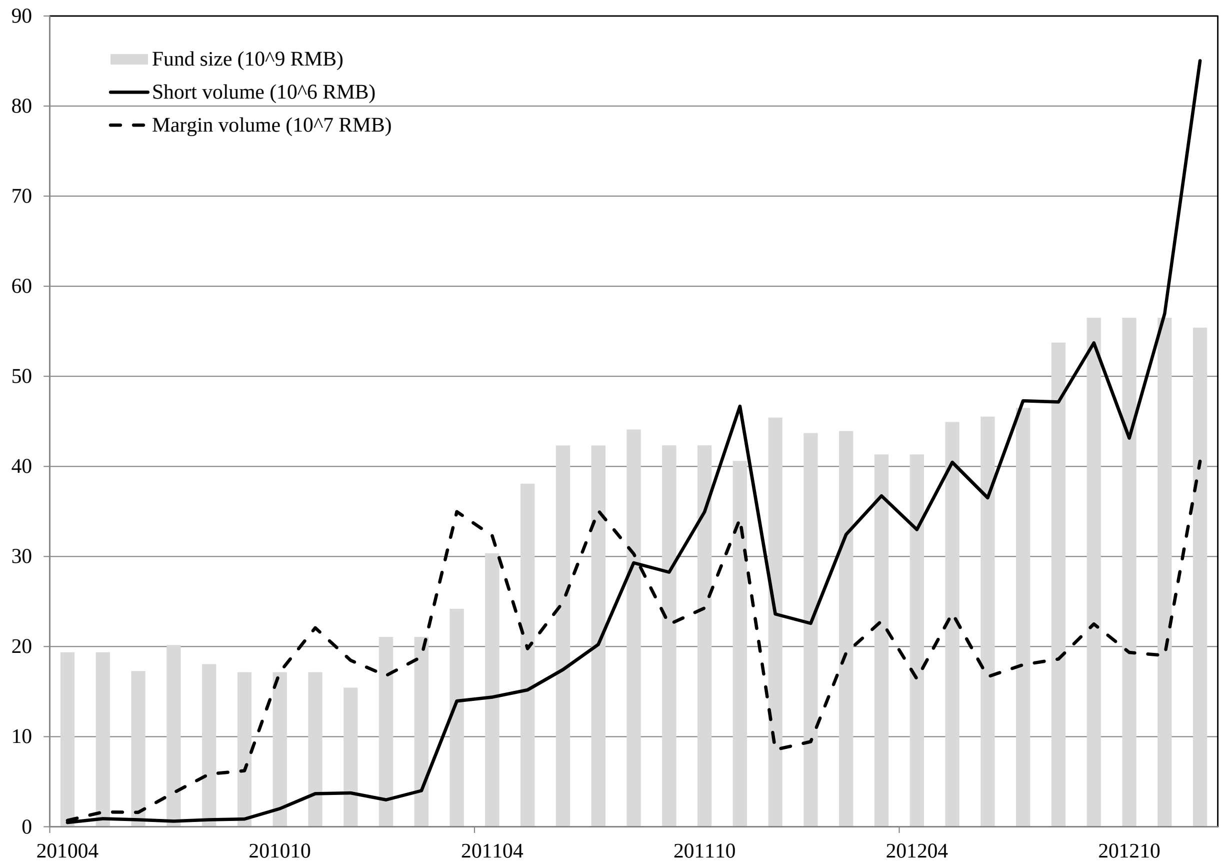

Figure 2: **The scale of principal-guaranteed fund**
This figure plots the book value of principal-guaranteed fund (in trillion RMB) in gray bar along the calendar time. It also plots the monthly trading volume of short-selling (in million RMB) in solid line and the margin-trading volume (in 10 million RMB) in dashed line.

Table 1: **Summary statistics: List changes, addition and deletion events**
This table reports statistics on the occurrence of events in which the bans on short-selling and margin-trading are lifted for a subset of Chinese stocks. We do not count ETF in this table. "Effective day" (yyyy/mm/dd) is the day on which a (revised) list of designated securities eligible for short-selling and margin-trading takes effect. "Announcement day" (yyyy/mm/dd) is the day on which the (revised) list is announced. The remaining columns show the number of stocks added to or deleted from the designated list and the number of stocks remaining on the list.

Effective day	Announcement day	No. added	No. deleted	No. on list
2010/03/31	2010/02/12	90	-	90
2010/07/01	2010/06/21	5	5	90
2010/07/29	2010/07/16	1	1	90
2011/12/05	2011/11/25	189	1	278
Cumulated		285	7	278

Table 2: **Stock returns around additions**
This table reports the cross-sectional average of (cumulated) abnormal returns along event time in trading days. An addition event is defined as one in which a stock is added to the designated list and therefore can be sold short or purchased on margin from the event day. The abnormal return is the raw return minus the market-model predicted return. In estimating the market model, we apply an estimation window of $[-396, -31]$ in calendar days relative to the announcement day, with a minimum length of 180 trading days. Panels A and B report statistics for the abnormal returns and the cumulative abnormal returns, respectively.

Event trading day	No. Obs.	Average return	t-value
Panel A: Daily abnormal returns around additions			
-5	260	-0.19%	-2.42
-4	271	-0.04%	-0.57
-3	272	-0.05%	-0.53
-2	272	-0.21%	-2.27
-1	272	-0.23%	-2.95
0	**274**	**-0.47%**	**-4.46**
1	274	0.17%	2.13
2	274	-0.09%	-1.15
3	274	-0.04%	-0.52
4	274	-0.10%	-1.14
5	274	-0.32%	-3.21
Panel B: Cumulative abnormal returns around additions			
$[-5, -1]$	272	-0.71%	-3.70
$[-1, +1]$	274	-0.53%	-3.13
$[0, +2]$	274	-0.39%	-2.34
$[0, +5]$	274	-0.85%	-3.54
$[0, +10]$	274	-1.59%	-3.97
$[0, +20]$	274	-3.60%	-6.06
$[0, +40]$	274	-3.15%	-5.20

Table 3: **Changes in efficiency and return distribution around additions**
This table reports the changes around addition events. In an addition event, an individual stock is added to the designated list and therefore can be sold short or purchased on margin from the event day. Column "Pre" shows the cross-sectional average of variables during the pre-event estimation window of [-56,-5] weeks relative to the addition event, and column "Post" shows the average in the post-event window of [5,56] weeks. We require a minimum of 36 weeks in the pre- and post-event windows to estimate the variables or to calculate the time-series average of variables, and a minimum of 16 weeks for variables conditional on signed returns. We apply the paired t-test to examine the statistical significance of the change in cross-sectional mean around the additions. In Panel A, we winsorize stock returns at two standard deviations around the mean. We estimate the OLS market model in the pre- and post-event estimation windows for each addition event and report statistics on β and R^2. We also estimate market models conditional on positive (negative) market returns. ρ is the cross-autocorrelation between stock returns and the lagged market returns, and ρ_+ (ρ_-) is estimated conditional on positive (negative) lagged market returns. In Panel B, *Volatility*, *Skew*, and *Kurt* are the standard deviation, skewness, and kurtosis of weekly returns. Vol_- (Vol_+) is the standard deviation of the minimum (maximum) of weekly returns and zero. $Extreme_-$ ($Extreme_+$) is the fraction of weekly returns lower (higher) than two standard deviations below (above) the mean. We do not winsorize returns to calculate return distribution measures in Panel B. Reported measures are winsorized at 1 and 99 percentile.

	N	Pre	Post	t-Ttest
Panel A: Change in efficiency				
β	276	1.19	1.27	4.78***
β_-	273	1.16	1.35	4.65***
β_+	278	1.30	1.29	0.24
R^2	276	48.2%	48.7%	0.51
R^2_-	273	30.7%	28.0%	3.73***
R^2_+	278	27.0%	24.9%	0.89
$\|\rho\|$	276	10.6%	9.1%	2.63***
$\|\rho_-\|$	276	23.1%	14.5%	8.52***
$\|\rho_+\|$	278	13.8%	12.3%	1.89*
$\|VR\|$	275	0.21	0.18	2.48***
Panel B: Change in return distribution				
Ret	275	0.08%	0.20%	-1.98*
Volatility	275	5.9%	4.9%	12.17***
$-Vol_-$	274	3.4%	2.9%	6.94***
$-Vol_+$	274	3.5%	2.8%	16.65***
Skew	275	0.13	0.26	2.59**
Kurt	274	1.04	0.99	0.31
$Extreme_-$	275	3.1%	1.2%	11.53***
$Extreme_+$	274	3.5%	2.3%	5.35***

Table 4: **Summary statistics for short-selling and margin-trading activities**
This table reports the summary statistics for daily short-selling and margin-trading activities. Average daily short volume (covering volume of short positions), in shares, is the cross-sectional average of the time-series average of the number of shares sold short (returned to cover the short positions) on each day for a given stock. Average daily short turnover (covering turnover of short positions) is the short (covering) volume scaled by daily trading volume. Average daily margin-trading volume (turnover) and covering volume (turnover) of margin positions are defined in a similar way.

	2010	2011	2012
No. of eligible stocks	96	278	278
Average daily short volume	4,468	61,560	130,841
Average daily short turnover	0.01%	0.59%	0.73%
Average daily covering volume of short positions	4,429	58,214	130,358
Average daily covering turnover of short positions	0.01%	0.55%	0.74%
Average daily margin purchase volume	306,647	509,981	930,217
Average daily margin purchase turnover	0.78%	3.58%	5.15%
Average daily covering volume of margin positions	246,174	401,271	858,115
Average daily covering turnover of margin positions	0.62%	2.36%	4.64%

Table 5: **Impact on efficiency and volatility**

This table reports the results of regressing efficiency and return distribution measures on short-selling and margin-trading turnovers, using stock-year panel data. In panel A, we winsorize stock returns at two standard deviations around the mean. R^2_- (R^2_+) is the R-square of the market model by regressing weekly returns on contemporaneous market returns in a stock-year, conditional on negative (positive) market returns. $|\rho_-|$ ($|\rho_+|$) is the absolute value of the cross-autocorrelation between weekly returns and lagged market returns in a stock-year, conditional on negative (positive) lagged market returns. $|VR|$ is the variance ratio, defined as the absolute value of the variance of monthly returns divided by four times the variance of weekly returns, minus one, in a stock-year. In Panel B, we do not winsorize stock returns. Vol_- (Vol_+) is the standard deviation of the minimum (maximum) of weekly returns and zero in a stock-year. $Extreme_-$ ($Extreme_-+$) is the fraction of weekly returns lower (higher) than two standard deviations below (above) the mean in a stock-year. $Skew$ is the skewness of weekly returns in a stock-year. $Short$, $Cover^{Short}$, $Margin$, and $Cover^{Margin}$ are daily short turnover, covering turnover of short positions, margin turnover, and covering turnover of margin positions, averaged to stock-year level. Control variables unreported for brevity include log firm size, yearly turnover ratio, dummy variables for dual-listed A-H stocks and A-B stocks. We winsorize variables at 1 and 99 percentile. The standard errors are clustered by year and stock. The t-statistics are reported in parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Impact on efficiency					
	R^2_-	R^2_+	$\|\rho_-\|$	$\|\rho_+\|$	$\|VR\|$
$Short$	-4.688**	0.074	-2.334	-2.237**	-1.407
	(2.18)	(0.04)	(0.82)	(2.01)	(0.76)
$Cover^{Short}$	-37.661	0.111	5.734	-32.202***	8.911
	(1.43)	(0.01)	(0.47)	(9.96)	(0.92)
$Margin$	-1.500	0.134	-0.998**	-0.969*	-1.376*
	(1.32)	(0.20)	(2.50)	(1.73)	(1.82)
$Cover^{Margin}$	3.913**	4.613***	-0.577	0.322*	-2.521
	(2.45)	(3.44)	(0.21)	(1.70)	(1.06)
N	457	457	457	457	457
$R^2 - adj$	14.5%	2.0%	16.1%	15.0%	9.5%
Panel B: Impact on return distributions					
	Vol_-	Vol_+	$Extreme_-$	$Extreme_+$	$Skew$
$Short$	0.066	0.195	-0.021	-0.060	-6.198
	(0.91)	(1.63)	(0.24)	(0.43)	(1.63)
$Cover^{Short}$	-4.160***	-4.310***	-2.725*	1.725	64.102
	(3.12)	(5.19)	(1.65)	(1.24)	(0.97)
$Margin$	-0.096***	-0.070*	-0.132**	-0.014	1.400
	(2.76)	(1.78)	(2.23)	(0.64)	(1.34)
$Cover^{Margin}$	0.033	-0.123	-0.224***	-0.192	0.783
	(0.61)	(1.46)	(5.08)	(1.11)	(0.86)
N	457	457	456	456	457
$R^2 - adj$	42.4%	30.8%	6.9%	-0.3%	1.5%

Table 6: **Determinants of short-selling and margin-trading activities**
This table reports the results of regressing daily short-selling turnover (*Short*), covering turnover of short positions ($Cover^{Short}$), margin-trading turnover (*Margin*), and covering turnover of margin positions ($Cover^{Margin}$) on past returns and other determinants using panel data. The turnovers are the respective trading volume in shares scaled by the daily total trading volume ×100. $r_{-5,-1}$ is the cumulative return for a stock in the past five trading days. r_t is the contemporaneous stock return. $spread_t$ is the volume-weighted effective spread on day t. $oimb_t$ is contemporaneous daily stock-level order imbalance, which is volume of buys minus sells scaled by the total volume of buys plus sells. We follow the buy and sell signs identified by GTA. $oimb^-$ equals $|oimb|$ if $oimb \leq 0$ and zero otherwise, and $oimb^+$ equals $oimb$ if $oimb \geq 0$ and zero otherwise. σ_t is daily high price minus low scaled by high. Other control variables not reported for brevity include the lagged dependent variable, the average share turnover in the past five trading days, the average sell- and buy-order imbalance in the past five trading days, the average σ in the past five trading days, log firm size, and book-to-market ratio. In columns (2) and (4), we control for the lagged short turnover and margin turnover, respectively. We winsorize variables at 1 and 99 percentile. The standard errors are clustered by calendar date and stock. The t-statistics are reported in parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	$Short_t$	$Cover_t^{Short}$	$Margin_t$	$Cover_t^{Margin}$
	(1)	(2)	(3)	(4)
$r_{-5,-1}$	-0.304***	-0.241***	-0.066	0.103
	(3.87)	(3.17)	(0.26)	(0.39)
r_t	0.868***	-1.296***	-5.676***	-1.644*
	(3.19)	(5.15)	(6.27)	(1.94)
$Spread_t$	0.002***	0.003***	0.007**	0.003
	(3.60)	(4.40)	(2.14)	(1.08)
$oimb_t^-$	-0.371***	-0.231***	1.065***	-0.770***
	(8.14)	(4.99)	(4.57)	(3.48)
$oimb_t^+$	0.011	-0.199***	-1.640***	-0.740***
	(0.23)	(4.29)	(9.80)	(4.30)
σ_t	2.432***	1.351***	-14.313***	-7.555***
	(5.47)	(3.58)	(10.58)	(5.70)
$TV_{-5,-1}$	-0.002***	-0.001**	0.000	-0.001
	(4.05)	(2.32)	(0.19)	(0.92)
N	65,369	65,339	65,369	65,360
$R^2 - adj$	52.3%	57.1%	46.4%	50.9%

Table 7: **Predicting future returns**

This table reports results of regressing future returns on short-selling and margin-trading activities using panel data. The dependent variable is the stock level (cumulative) abnormal returns on day $t+2$, from trading days 2 to 5, 2 to 10, or 2 to 20. The abnormal return is raw return adjusted by the market-model, which is estimated in a rolling window of $[-280, -31]$ trading days. *Short*, $Cover^{Short}$, $Margin$, and $Cover^{Margin}$ are the respective short-selling turnover, covering turnover of short positions, margin-trading turnover, and covering turnover of margin positions. Turnovers are the respective trading volume in shares scaled by the daily total trading volume. $r_{-5,-1}$ is the cumulative return for a stock in the past five trading days. r_t is the contemporaneous stock return. $spread_t$ is the time-weighted bid-ask spread on day t. $oimb_t$ is contemporaneous daily order imbalance of a stock, which is volume of buys minus sells scaled by the total volume of buys plus sells. We follow the buy and sell signs identified by GTA. $oimb^-$ equals $|oimb|$ if $oimb \leq 0$ and zero otherwise, and $oimb^+$ equals $oimb$ if $oimb \geq 0$ and zero otherwise. σ_t is daily high price minus low price scaled by high price. Other control variables unreported for brevity include the average share turnover in the past five trading days, log firm size, and book-to-market ratio. The standard errors are clustered by calendar date and stock. The t-statistics are reported in parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	CAR_{+2}	$CAR_{+2,+5}$	$CAR_{+2,+10}$	$CAR_{+2,+20}$
$Short_t$	-0.022*	-0.045*	-0.033	-0.013
	(1.75)	(1.72)	(0.79)	(0.18)
$Cover_t^{Short}$	0.050***	0.141***	0.222***	0.284***
	(3.64)	(5.80)	(4.73)	(3.70)
$Margin_t$	-0.003	-0.005	-0.009	-0.010
	(1.58)	(0.95)	(0.78)	(0.50)
$Cover_t^{Margin}$	0.002	-0.001	0.000	-0.002
	(1.00)	(0.14)	(0.04)	(0.08)
$r_{-5,-1}$	-0.131	-0.915	-1.943*	-4.632***
	(0.76)	(1.49)	(1.77)	(3.14)
r_t	0.695	1.385	0.849	-2.715
	(1.51)	(1.19)	(0.47)	(1.37)
$Spread_t$	0.001	0.007**	0.013*	0.021
	(0.77)	(2.17)	(1.88)	(1.63)
$oimb_t^-$	0.122	0.200	-0.154	-0.443
	(1.31)	(1.04)	(0.50)	(0.90)
$oimb_t^+$	-0.376***	-0.826***	-1.164***	-1.563**
	(3.41)	(3.35)	(3.15)	(2.57)
σ_t	2.661***	6.371***	8.003**	13.424***
	(3.94)	(3.42)	(2.47)	(2.64)
N	52,349	52,349	52,349	52,349
$R^2 - adj$	0.21%	0.46%	0.52%	0.52%

Table 8: **Potential trading motivations: Technical analysis**
This table reports the results of regressing daily short-selling and margin-trading turnovers on technical indicators using panel data. In Panel A, we rank stocks by the cumulative returns in the past five trading days ($r_{-5,-1}$), and dummy $loser_{-5,-1}$ ($winner_{-5,-1}$) equals one for stocks in the bottom (top) quintile and zero otherwise. Dummy $down_{-1}^{MA}$ (up_{-1}^{MA}) equals one if the closing price on day $t-1$ goes down (up) and crosses over the past 20 trading day's moving average from above (below) and zero otherwise. Dummy $down_{-1}^{TRB}$ (up_{-1}^{TRB}) equals one if the closing price on day $t-1$ goes down (up) and breaks through the trading range of the past 250-trading day's minimum (maximum) and zero otherwise. In panel B, we redefine technical indicators based on the contemporaneous stock return (r_t). Control variables unreported for brevity include the lagged dependent variable, the contemporaneous bid-ask spread, sell/buy order imbalance, σ, and the historical average turnover ratio, sell/buy order imbalance, σ in the past five trading days, log firm size, and book-to-market ratio. In columns (2) and (4), we control for the lagged short turnover and margin turnover, respectively. We winsorize variables at 1 and 99 percentile. The standard errors are clustered by calendar date and stock. The t-statistics are reported in parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	$Short_t$ (1)	$Cover_t^{Short}$ (2)	$Margin_t$ (3)	$Cover_t^{Margin}$ (4)
Panel A: Regressing on past technical indicators				
$loser_{-5,-1}$	0.021***	0.014**	0.043	0.040
	(3.03)	(2.22)	(1.52)	(1.45)
$winner_{-5,-1}$	0.000	0.002	0.027	0.035
	(0.06)	(0.31)	(1.03)	(1.22)
$down_{-1}^{MA}$	0.072***	0.043***	-0.086	-0.097**
	(4.29)	(3.17)	(1.29)	(1.98)
up_{-1}^{MA}	-0.094***	-0.069***	-0.067	-0.034
	(7.45)	(5.47)	(1.30)	(0.70)
$down_{-1}^{TRB}$	0.042**	0.023	-0.158***	-0.073
	(2.14)	(1.48)	(2.72)	(1.17)
up_{-1}^{TRB}	-0.109***	-0.063*	-0.203	-0.136
	(3.14)	(1.71)	(1.57)	(1.51)
r_t	1.423***	-1.034***	-8.106***	-2.048**
	(5.19)	(4.01)	(7.96)	(2.56)
N	65,945	65,915	65,945	65,936
$R^2 - adj$	51.9%	56.9%	45.4%	50.8%
Panel B: Regressing on contemporaneous technical indicators				
$r_{-5,-1}$	-0.326***	-0.259***	0.221	0.175
	(4.23)	(3.40)	(0.82)	(0.66)
$loser_t$	-0.057***	0.012**	0.179***	-0.196***
	(7.03)	(1.99)	(5.13)	(6.40)
$winner_t$	0.192***	0.025***	-0.568***	-0.193***
	(15.28)	(2.73)	(13.51)	(6.35)
$down_t^{MA}$	-0.031***	0.015	0.049	0.021
	(2.88)	(1.31)	(0.71)	(0.35)
up_t^{MA}	-0.014	-0.060***	-0.216***	-0.009
	(0.81)	(3.81)	(3.97)	(0.18)
$down_t^{TRB}$	0.064***	-0.004	-0.204***	0.009
	(3.74)	(0.27)	(3.37)	(0.13)
up_t^{TRB}	-0.132***	-0.130***	-0.095	-0.168**
	(5.33)	(3.40)	(0.78)	(1.98)
N	65,945	65,915	65,945	65,936
$R^2 - adj$	52.7%	56.9%	45.6%	50.8%

Table 9: **Identity of short-sellers and margin-traders**

Based on transaction data, we label trade records with average dollar volume greater than or equal to RMB 50,000 as "large", those with average dollar volume greater than or equal to RMB 10,000 but less than RMB 50,000 as "middle", and those with average dollar volume less than 10,000 as "small" (Ng and Wu, 2007). We follow the buy or sell signs identified by GTA. Panel A shows the distribution of the number and dollar volume of trades assigned to groups. Panel B reports the results of regressing the excel buy and sell by different groups on the past return ($r_{-5,-1}$) and contemporaneous return r_t. Control variables unreported for brevity include past order imbalance $oimb_{-5,-1}$, bid-ask spread $spread_t$, daily volatility σ_t, past turnover $tv_{-5,-1}$, firm size, and book-to-market ratio. Panel C reports the results of regressing daily short-selling turnover ($Short_t$), covering turnover of short positions ($Cover_t^{Short}$), margin-trading turnover ($Margin_t$), and covering turnover of margin positions ($Cover_t^{Margin}$) on the contemporaneous excess buy or sell from different groups. Control variables unreported for brevity include the lagged dependent variables. Panel D reports the results of regressing future (cumulative) abnormal return on excess buy or sell from different groups. Control variables unreported for brevity include $r_{-5,-1}$, r_t, σ_t, and $tv_{-5,-1}$. We winsorize variables at 1 and 99 percentile. The standard errors are clustered by calendar date and by stock. The t-statistics are reported in parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Large Buy (1)	Sell (2)	Middle Buy (3)	Sell (4)	Small Buy (5)	Sell (6)
Panel A: Summary statistics by different investor groups						
No. of trades ($\times 10^6$)	1.384	1.357	14.494	13.874	6.185	6.147
	3.2%	3.1%	33.4%	31.9%	14.2%	14.2%
Value of trades ($\times 10^{12}$)	1.263	1.238	3.069	2.954	0.387	0.381
	13.6%	13.3%	33.0%	31.8%	4.2%	4.1%
Panel B: Regress excess-buy or sell by investor groups on past and contemporaneous returns						
$r_{-5,-1}$	-0.032*	0.004	0.014	0.022**	-0.001	0.025***
	(1.88)	(0.25)	(1.02)	(1.98)	(0.12)	(2.63)
r_t	-0.173***	0.037	0.276**	-0.044	-0.063	0.030
	(3.26)	(0.81)	(2.45)	(0.41)	(0.97)	(0.43)
Panel C: Regress short-selling/margin-trading on excess buy/sell						
$Short_t$	0.034	0.126***	0.561***	-0.244***	0.064	-0.018
	(0.73)	(2.64)	(6.84)	(3.86)	(0.70)	(0.24)
$Cover_t^{Short}$	0.056	0.084**	-0.112*	-0.098**	0.047	-0.038
	(1.50)	(2.04)	(1.74)	(1.98)	(0.59)	(0.49)
$Margin_t$	0.276	-0.018	-2.379***	0.677**	-0.092	-0.016
	(1.38)	(0.11)	(8.87)	(2.55)	(0.27)	(0.05)
$Cover_t^{Margin}$	0.011	0.201	-0.518***	-1.206***	-0.246	-0.133
	(0.05)	(1.05)	(2.65)	(4.12)	(0.68)	(0.35)
Panel D: Regress future return on excess buy/sells						
CAR+2	0.029	0.114	-0.270	0.482***	-0.246	-0.505***
	(0.30)	(1.15)	(1.61)	(3.02)	(1.30)	(3.01)
$CAR_{+2,+5}$	0.012	0.438*	-0.303	0.635**	0.130	-0.259
	(0.05)	(1.87)	(0.79)	(2.11)	(0.26)	(0.67)
$CAR_{+2,+10}$	-0.082	0.467	-0.073	0.516	-0.028	-0.734
	(0.25)	(1.47)	(0.13)	(1.19)	(0.04)	(1.27)
$CAR_{+2,+20}$	-0.432	-0.008	0.288	1.015	-0.459	0.662
	(0.90)	(0.02)	(0.34)	(1.24)	(0.37)	(0.65)

Table 10: **Subsample analysis**

We divide the whole sample period to two subsamples: an early period from March 2010 to June 2011, and a recent period from July 2011 to December 2012. We regressing future returns on short-selling and margin-trading activities using panel data. The dependent variable is the stock level (cumulative) abnormal returns on day $t+2$, from trading days 2 to 5, 2 to 10, or 2 to 20. The abnormal return is raw return adjusted by the market-model, which is estimated in a rolling window of $[-280, -31]$ trading days. $Short$, $Cover^{Short}$, $Margin$, and $Cover^{Margin}$ are the respective short-selling turnover, covering turnover of short positions, margin-trading turnover, and covering turnover of margin positions. Turnovers are the respective trading volume in shares scaled by the daily total trading volume. Control variables unreported for brevity include the cumulative stock return in the past five trading days, the contemporaneous return, the contemporaneous effective spread, the contemporaneous buy- and sell-order imbalance, volatility, the average share turnover in the past five trading days, log firm size and book-to-market ratio. The standard errors are clustered by calendar date and stock. The t-statistics are reported in parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	CAR_{+2}	$CAR_{+2,+5}$	$CAR_{+2,+10}$	$CAR_{+2,+20}$
Panel A: The early subperiod: March 2010 - June 30, 2011				
$Short_t$	-0.076	-0.020	-0.126	0.036
	(1.42)	(0.17)	(0.71)	(0.10)
$Cover_t^{Short}$	0.139**	0.261***	0.575***	0.508*
	(2.27)	(2.85)	(3.78)	(1.91)
$Margin_t$	0.002	0.003	-0.005	0.054
	(0.40)	(0.19)	(0.19)	(1.11)
$Cover_t^{Margin}$	-0.006	-0.017	-0.012	-0.048
	(1.12)	(1.20)	(0.47)	(0.99)
N	22,250	22,250	22,250	22,250
R^2-adj	0.36%	0.67%	0.81%	0.82%
Panel B: The recent subperiod: July 2011 to December 2012				
$Short_t$	-0.022*	-0.053**	-0.035	-0.018
	(1.69)	(1.99)	(0.90)	(0.26)
$Cover_t^{Short}$	0.044***	0.134***	0.204***	0.287***
	(3.18)	(5.31)	(4.25)	(3.74)
$Margin_t$	-0.004*	-0.008	-0.013	-0.023
	(1.88)	(1.28)	(1.01)	(0.96)
$Cover_t^{Margin}$	0.003	0.000	-0.002	0.003
	(1.27)	(0.03)	(0.14)	(0.12)
N	30,099	30,099	30,099	30,099
R^2-adj	0.14%	0.48%	0.44%	0.43%