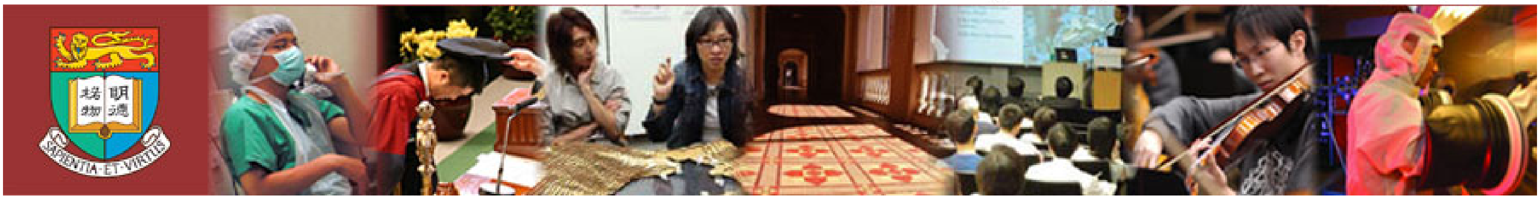

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Short-selling, margin-trading, and price efficiency: Evidence from the Chinese market

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Abstract

China launched a pilot scheme in March 2010 to lift the ban 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 ban is lifted, price efficiency increases while stock return volatility decreases. Panel data regressions reveal that intensified short-selling activities are associated with improved price efficiency. Short-sellers trade to eliminate overpricing by selling stocks with higher contemporaneous returns following a downward trend, and their trades predict future returns. In contrast, we find intensified margin-trading activities for stocks with lower contemporaneous returns, and these trades have no return predictive power.

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1. Introduction

The impact of the short-sale constraint on the capital market is highly controversial. There is intense debate over whether this constraint induces an upward bias in asset valuations, reduces price efficiency, and/or stabilizes the market (Miller, 1977; Diamond and Verrecchia, 1987; Hong and Stein, 2003). Ever 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 even greater 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 ban on short-selling and margin-trading was lifted for a subset of stocks overnight. We then test whether the short-sale constraint contributes to share overvaluation by examining the event returns (Chang et al., 2007). Second, we investigate whether the constraints hinder price discovery and/or stabilize the market by examining the changes in price efficiency and return volatility after the ban is lifted (Bris et al., 2007). Third, China makes the daily short-selling, margin-trading, and associated covering volume data publicly available at the stock level. U.S. researchers, in comparison, usually observe the monthly short interest only. We further examine the relation between price 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 to 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 observe 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 the short-sale constraint contributes to share overvaluation.

Second, we obtain the weekly returns over a one-year period both before and after the event and estimate efficiency measures. The results show that after the bans are lifted, stock return synchronicity (R^2) decreases significantly in the down-market. The cross-autocorrelation (ρ) between stock returns and lagged market returns decreases significantly in both the up- and down-market, but the magnitude of change is much larger in the down-market. Variance ratio also drops significantly. These results indicate that short-selling and/or margin-trading improve price efficiency, especially during market downturns. We then investigate the change in the distributions of weekly returns. We observe significantly lower return volatility in both the up- and down-market and lower frequency of extreme stock returns after the bans are lifted. This contradicts traditional wisdom that short-sellers and/or margin-traders destabilize the market.

Third, we utilize panel data on short-selling and margin-trading activities to examine the impact of these activities on price efficiency. We find that intensified short-selling activities are associated with lower down-market return synchronicity (R^2_-) and lower up-market cross-correlation (ρ_+). The covering of short positions is also associated with lower ρ_+. The results imply that short-selling improves price efficiency. Margin traders' contribution to price efficiency, however, is mixed. Whereas margin-trading turnover is negatively associated with the cross-correlation and variance ratio, the covering of margin position is positively associated with return synchronicity and up-market cross-correlation. Overall, the purchase decisions of margin-traders increase price efficiency and their sell decisions reduce 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-markets, 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 the stock level to infer the trading motivations and to assess the informativeness of Chinese short-sellers and margin-traders. We observe intensified short-selling activities for stocks with low historical return and high contemporaneous return. This result indicates that short-sellers arbitrage against very short-term price rebounds following an established downward trend. Intensified short-selling activities have no observable association with buy-order imbalance, refuting the alternative trading motivation of liquidity provision. Intensified short-selling is accompanied by lower sell-order imbalance, suggesting that the trading strategies adopted by short-sellers differ from those of other typical sellers. In addition, intensified short-selling accompanies higher intraday volatility and higher spread, indicating that short-sellers are potentially informative investors. In short, we find that short-sellers trade on temporal over-pricing following a downward trend. In comparison, margin-trading and associated covering turnover show no discernible relation with historical returns. We find some tentative evidence that margin-traders buy underpriced stocks, but the covering of short positions is not triggered by the reversal of underpricing. We also find evidence that margin-traders provide liquidity to stocks with higher 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 higher sell-order imbalance, indicating that the liquidity provision by margin-traders is not profitable.

We then explore whether trades by short-sellers or margin-traders predict future stock returns. Surprisingly, we find that short-selling activities marginally predict future returns over up to five trading days, and the covering activities of short positions have very strong return predictive power even over 20 trading days ahead. Margin-trading activities, however, show no return predictive power. These results suggest that short-sellers possess the ability to identify the temporal price rebounds following a downward trend.

Utilizing intraday transaction data, we categorize trades into small, middle-size, and large trades according to the average dollar volumes. We find that short-sellers tend to trade in large size, and they trade opposite to middle-size trades. The trades of margin-traders do not fall into any specific size category, but margin-traders also trade opposite to middle-size trades. This partially explains why short-selling and margin-trading activities do not add to return volatility.

This study contributes to the literature in several aspects. First, it provides additional evidence on the impact of short-selling and margin-trading constraints on the market. Second, to the best of our 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 explore the trading strategies adopted by Chinese short-sellers and margin-traders. This study helps market participants to understand why, when, and how those special investors trade. The findings in this study provide important policy implications for 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 have attempted to lift restrictions on the financial market, whereas they are still concerned about 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 implemented the pilot scheme of "refinancing" in August 2012, allowing banks, mutual funds, and insurance companies to lend out money to margin-traders, contributing to the soaring volume of margin-trading. "Security refinancing", however, was shelved due to 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 information producers. We thus urge upon 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 good news about the underlying firm. If the news is extraordinarily positive and precise, she may build up a leveraged position by borrowing capital from a broker (margin-trading) or from other resources. However, she has difficulties in selling the stock short if she has bad news. Short-selling, the trading activity of selling a borrowed stock without owning it, may be prohibited by law in some countries, not be practiced due to a lack of stock lenders or high security-lending fees, or be 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 share overvaluation

Miller's (1977) seminal model predicts overvaluation to be 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 already consider this constraint in a rational-expectations 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, they 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 support 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 among 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 used is the cross-autocorrelation between stock returns and signed lagged market returns. Based on these two efficiency measures, they 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, price delay, and variance ratio to measure efficiency. They utilize proprietary data on stock lending and loan fees from 26 countries and find lower efficiency for stocks with more binding short-sale constraints. Similarly, Chen and Rhee (2010) document a more rapid price adjustment for shortable stocks than for non-shortable stocks in Hong Kong.

The U.S. government banned short-sale in September 2008 following the disastrous subprime crisis. 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 leads to more negatively skewed returns. The empirical results are also mixed. Bris et al. (2007) find that in countries where short-selling is either not allowed or not 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 increased occurrences 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 increased occurrences of negative returns, which does not support the stabilization function. Boehmer et al. (2013) find that the U.S short-sale ban in September 2008, which was intended to stabilize the turbulent capital markets, fails to support prices. Furthermore, the ban demonstrates side-effects by reducing liquidity, slowing down price discovery, and impeding market-making for options.

2.3. Short-selling activity and returns

Despite ample vivid stories about "evil" short-sellers' wrongdoings in the long history of finance (Bris et al., 2007), there is still a hot debate over the relation between short-selling and past/subsequent returns. Empirical investigations into short-sellers' trading motivation, strategy, or profitability are scarce. Lack of data is the greatest limitation. The commonly used data in U.S. are the monthly short interest (e.g., Figlewski, 1981; Karpoff and Lou, 2010). Distinct from the short volume, which is the number of shares sold short during the period, the short interest denotes the open short positions at the end of the period. 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 not updated after this scheme ended in 2007. Some researchers are able to obtain proprietary data at the daily frequency or at the transaction level, even with some clues regarding the identity of traders (e.g., Boehmer et al., 2008; Cohen et al., 2007). 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 the regulated SHO data at the transaction level. They observe higher short-selling volume following positive returns, and that short-selling positively predicts future returns over the five-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 aforementioned findings raise the question of why short-sellers are able to predict future returns. Diether et al. (2009) offer four potential explanations. First, short-sellers may possess insider information, especially negative private information. Many studies find supporting evidence for this hypothesis. For example, Karpoff and Lou (2010) document an increase in short-selling activity at least one year before a financial misconduct is publicly revealed. Second, short-sellers tend to be sophisticated investors, who are more capable of identifying overpriced stocks. In line with this conjecture, Boehmer et al. (2008) report that 74% of short-selling orders are executed by institutions, and less than 2% are executed 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 positions at a profit. Fourth, short-sellers may be speculators in voluntarily bearing more risk during periods of high uncertainty. If high uncertainty results from information asymmetry, intensified short-selling should coincide with higher spread, which falls after the information gets public. If high uncertainty results from divergent opinions, intensified short-selling should coincide with lower spread owing to 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. The Chinese stock market is one of the most important developing markets. We are thus curious to know the nature of Chinese short-sellers and margin-traders, their trading strategies, whether they are profitable or not, and whether or not their trades contribute to market efficiency and/or destabilize the market.

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-making 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 of October 1987, regulatory bodies have tended to propose more stringent margin requirements to intimidate speculators. Chowdhry and Nanda (1998), however, develop a model that predicts increased market instability brought about by the margin requirements themselves. Since the security purchased on margin serves as a 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) observes no higher volatility, improved liquidity, and increased price informativeness after margin-trading is allowed for U.S. OTC stocks. In contrast, Hardouvelis and Peristiani (1992) find that a higher margin requirement in Japan deters speculators and does not incur market instability. Interestingly, Hirose et al. (2009) find that although retail investors, who are presumably uninformed, dominate margin-trading in Japan, their trades positively predict future returns, especially for small firms.

3. Market reactions

3.1. Institutional background

Short-selling and 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 and/or to 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 existing 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.[4] 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.[5] Similar to the practice in Japan and Taiwan, short-selling and margin-trading business in China seems to caters to retail investors rather than to 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

[4] First, to be eligible for margin-trading, a firm must have no fewer than 100 million tradable shares and a public float no less than RMB 500 million (US$79.5 million). To be eligible for short-selling, a firm must have no fewer than 200 million tradable shares and a public float no less than RMB 800 million (US$127.3 million). Second, the number of shareholders must be no fewer 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. Source: http://www.sse.com.cn/cs/zhs/xxfw/flgz/rules/sserules/sseruler20111125b.html.

[5] Taking the guidance of Haitong Securities as an example, qualified investors must satisfy the following requirements. The investor has 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 less than RMB 500,000 (approximately US$79,500). The investor must demonstrate the basic investment knowledge by passing a professional knowledge 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.

Securities charges 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. The prime rate for 6-month loans (published by The People's Bank of China) was 5.60% on December 31, 2012. Haitong thus charged 8.60% for margin-trading and stock-lending. Huatai Securities, however, charged 8.60% for margin-trading and 10.60% for security lending. In sharp contrast, D'Avolio (2002) reports that the value-weighted loan fee 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 average fee is only 4.3%. The limited supply of security lending is also a problem in China. From March 2010 to August 2012, qualified investors could borrow money or stock only from security companies. After August 27, 2012, investors can also borrow money from investment banks, funds, and insurance companies through a centralized refinancing company. Security lending, unfortunately, 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.

3.2. Data

We collect information on the designated stock list from the exchange websites[6]. 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 the respective covering volumes for eligible stocks from WIND.

The sample period spans from January 1, 2010 to December 31, 2012. We have 285 stock

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

addition events, 10 ETF addition events, and 7 deletion events in this period. We exclude the 7 deletion events as such events constituent an extremely small sample. Due to the special features of ETFs and lack of data, we also exclude 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 belong to the second major batch added on December 5, 2012. Table 1 reports the event distributions. 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 the market-model adjusted abnormal returns around the addition events. 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/or 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.[7] We estimate the abnormal return for stock i by regressing its 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 the value-weighted return of all stocks traded in the A-share market, using the market capitalization of the public float as the weight. We then calculate the market-model adjusted abnormal return $AR_i^m(t)$ for stock i on day t as $AR_i(t) = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{Mt}$, where α and β are estimated from the market model regression. We calculate the cumulative abnormal return during the event window $[t_1, t_2]$ 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 an average abnormal

[7] 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.

return of -47 bps on the event day, which is significantly negative. In Panel B, $CAR[-5,-1]$, the abnormal return cumulated during the five trading days before the event, is -71 bps on average, which is significantly negative. As the addition event is known by the public, selling activities in advance may push this pre-event price drop. $CAR[0,2]$ is -39 bps on average and $CAR[0,5]$ is -85 bps on average, both significantly negative. The average CAR 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 observe negative ARs on most days and a downward trend in CAR throughout the window. The negative cumulative return is persistent and not followed by any evident reversal, consistent with the results in Table 2.

In summary, stock returns realized upon the implementation of short-selling and margin-trading tend to be negative. Sharif et al. (2012) report consistent evidence when examining 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. Therefore, upon the lifting of the bans, the overvaluation caused by short-selling bans leads to the observed price drop, supporting Miller's (1977) share overvaluation hypothesis.

3.4. Changes in price efficiency

We next examine whether the short-selling and margin-trading constraints hinder price discovery by examining the changes in price efficiency measures around the addition events. We obtain weekly returns over 56 weeks both before and after the addition events and apply a pre-event window of $[-56,-5]$ weeks and a post-event window of $[+5,+56]$ weeks relative to the event week, skipping for one month, to estimate efficiency. We winsorize stock returns that are more than three standard deviations away from the mean.

We estimate three efficiency measures based on weekly stock returns. 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. A higher β indicates a greater sensitivity of stock returns in response to market-wide information. A lower R^2 indicates higher efficiency as prices incorporate more firm-specific information. We also estimate the market model conditional on negative (positive) market returns, and denote beta as β_- (β_+) and R-squared 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. A higher ρ indicates a greater delay and thus lower price efficiency. Third, following Saffi and Sigurdsson (2011), we estimate the variance ratio ($|VR|$) in a rolling manner, defined as the absolute value of the variance of monthly returns divided by four times the variance of weekly returns minus one. A higher $|VR|$ indicates lower price efficiency, as the return process deviates more from a random walk.[8] We require a minimum of 36 weeks in each estimation window to calculate the unconditional efficiency measures and a minimum of 16 weeks to calculate the signed efficiency measures. We then perform paired t-tests to examine the change in price efficiency around the addition events.

Panel A of Table 3 shows the comparison results. We find that β_- increases significantly after the bans are lifted, indicating that stock returns are more sensitive to negative information after short-selling and margin-trading are implemented. R^2_- drops significantly, suggesting more firm-specific information incorporated into stock prices in the down-market, and thus greater price efficiency. Both $|\rho_-|$ and $|\rho_+|$ drop significantly, with $|\rho_-|$ decreasing from an average of 23.1% to 14.5%. $|VR|$ also drops significantly, indicating less deviation from a random walk process. All these pieces of evidence show improving price efficiency after short-selling and margin-trading are implemented. Moreover, the improvement in price efficiency is more evident in the down-market. The evidence hints that it is the short-selling constraint that hinders price discovery and that it is short-selling activities that contribute to greater efficiency. We will perform additional cross-sectional test in Section 4.2 to further investigate the relation between efficiency and short-selling/margin-trading activities.

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

3.5. Changes in return distributions

We next investigate the change in return distributions (Chang et al., 2007; Bris et al., 2007). For each stock i, we obtain volatility, skewness, and kurtosis of weekly returns (R_{it}) in the pre- and post-event estimation window, respectively. In addition, we calculate the standard deviation of $max(R_{it}, 0)$ as up-side volatility (Vol_+) and the standard deviation of $min(R_{it}, 0)$ as down-side volatility (Vol_-). $Extreme_-$ ($Extreme_+$) is the occurrence of extremely negative (positive) returns, defined as the fraction of weeks in which returns are two standard deviations below (above) the average for each stock. Different from Section 3.4, we do not winsorize weekly stock returns in this section. 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 frequency of extreme returns after the addition events.

Panel B of Table 3 reports the comparison results. Contrary to the notion that short-selling and margin-trading undermine market stabilization, we observe lower down-side and up-side volatility, higher skewness, and fewer occurrences of extremely positive and negative returns after short-selling and margin-trading are implemented. These results show that the trades by Chinese short-sellers and margin-traders even stabilize the market. This evidence contradicts the U.S. evidence (Bris et al., 2007) and Hong Kong evidence (Chang et al., 2007), but is consistent with the international evidence of Saffi and Sigurdsson (2011). We will discuss the possible explanations for this phenomenon in Sections 5.1, 5.2, and 6.2.

4. Short-selling and margin-trading activities

As we discuss in Section 2.3, China makes panel data on daily short-selling and margin-trading volume data publicly available, allowing us to perform more powerful cross-sectional tests. In this section, we further investigate the relation between price efficiency and the short-selling and margin-trading activities.

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. These two panels reveal that short-selling and margin-trading are becoming popular over the years. For example, the average daily short volume as a percentage of daily trading volume is only .01% in 2010 and increases to .73% in 2012. The average daily margin volume as a percentage of trading volume is .78% in 2010 and increases to 5.15% in 2012. Margin-trading is more popular than short-selling for several reasons. 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 the supply of capital in margin-trading, especially after the refinancing mechanism was implemented in August 2012. Third, the up-tick rule adds to the difficulties of short-selling. Fourth, short-selling itself is riskier than margin-trading as it could induce unlimited losses. Finally, as Chinese investors are new to the short-selling mechanism, it is not surprising that unsophisticated investors 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 annual efficiency measures at the stock level based on weekly returns. We also obtain the annual average of daily short-selling and margin-trading turnovers and associated covering turnovers for each stock, where daily turnovers are defined as the daily short/margin/covering volume scaled by daily total trading volume. The annualized covering of short (margin) turnover is extremely highly correlated with short (margin) turnover itself. To address the concern of multicollinearity, we regress covering of short (margin) turnover on short (margin) turnover and take the residual as orthogonalized covering turnover. Utilizing this panel data, we regress price efficiency and return distribution 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, annualized share turnover ratio, dummy variables for dual-listed A-H stocks and A-B stocks. Following Thompson (2011), we use the standard errors clustered by stock and year to deal with potential serial correlation across firms and over time.

Table 5 reports the regression results. Panel A shows that intensified short-selling activity is associated with lower down-market R^2, indicating that more firm-specific bad news is incorporated into stock prices accompanying intensified short-selling activities. Besides, intensified short-selling and covering activities are associated with lower up-market cross-correlation, suggesting that short-selling even facilitates the discovery of positive information. Overall, intensified short-selling activities are associated with improved price efficiency. The effect of margin-trading activities, however, is ambiguous. Intensified margin-trading activities are associated with higher price efficiency, indicated by lower cross-correlation in both up- and down-market and lower variance ratio. Intensified covering activities of margin positions, however, are associated with lower efficiency, indicated by significantly higher R^2 in both up- and down-markets and higher up-market cross-correlation. We do not report the coefficients on control variables for the sake of brevity.

We next examine the impact of short-selling/margin-trading activities on the distribution of stock returns. Panel B of Table 3 shows that intensified purchase activities, induced by margin-trading and/or the covering of short positions, are associated with lower up- and down-side volatility and fewer occurrences of extremely negative returns. Even the selling activity induced by the covering of margin positions is associated with fewer occurrences of extremely negative returns. These results contradict traditional wisdom that short-sellers and margin-traders speculate on private information and destabilize the market. We will explore their trading strategies in Sections 5.1 and 5.2.

5. Trading strategies and return predictability

Next, we proceed to infer the trading strategies deployed by Chinese traders using data on the daily trading activities of short-sellers and margin-traders.

5.1. Trading strategies adopted by short-sellers

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 daily short-selling turnover ($Short_t$) at stock level on the historical stock return cumulated over the past five trading days ($r_{-5,-1}$) and the contemporaneous return (r_t). If Chinese short-sellers adopt the same trading strategies as their U.S. counterparts, we expect the coefficients on both $r_{-5,-1}$ and r_t to be positive. As the Augmented Dickey-Fuller test rejects the existence of a unit root in the series of daily short turnovers, 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 of 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%. The magnitude is not trivial given that the average daily short turnover in 2012 is just .73% (Table 4). These results suggest that Chinese short-sellers also arbitrage against overpricing. The overpricing, however, is a very temporal price rebound following low returns in the past week. Chinese short-sellers appear to believe in the persistence of trends implied by historical returns. They believe that a positive return following a downward trend, therefore, is temporal and will be reversed very soon. The causal relation between r_t and $short_t$ cannot be argued the other way around, 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 cover the short position in reversed buy-imbalance. The order imbalance ($oimb$) 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. Table 6 shows no evidence supporting the liquidity provision hypothesis, as short-selling turnover has no observable relation with the buy-order imbalance. The short-selling and margin-trading volumes are included in the transaction data in calculating the buy/sell imbalance. Therefore, intensified short-selling turnover should be associated with higher sell-order imbalance by construction. The observed negative association between short-selling turnover and sell-order imbalance suggests that short-sellers avoid trading when other sellers sell heavily, and/or short-sellers sell heavily when other sellers are mute. To be brief, short-sellers trade opposite to other typical sellers.

To examine the opportunistic risk-bearing hypothesis, we use daily volatility (σ) to measure uncertainty, which is defined as the difference in the daily high and low price divided by the high price. We use *spread*, the volume-weighted average of the effective spreads on a day, to discriminate between the information asymmetry and divergence opinions hypotheses. Column (1) of Table 6 shows that intensified short-selling is accompanied by higher volatility and higher spread, indicating short-sellers' risk-bearing trading under increased uncertainty induced by information asymmetry. The evidence is also consistent with the hypothesis that short-sellers possess private information and thus their trades result in increased uncertainty and increased spread.

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

Column (2) of Table 6 reports the regression results with $Cover^{Short}$ as the dependent variable. The coefficient on $r_{-5,-1}$ is significantly negative, similar to that in column (1).

This suggests that the duration of this short position is likely to be quite short. The negative coefficient on r_t supports the overpricing hypothesis as short-sellers cover the short positions after the "temporal" overpricing is reversed. To maximize the profit of the short positions, investors should hold the short position till the upturn emerges. If short-sellers successfully time the market, intensified covering of short-selling positions should predict superior future returns. We will investigate this return predictive power in Section 5.3. Further, we observe a negative relation between the covering of short positions and the buy and sell-order imbalance. It suggests that short-sellers make the covering decisions on a day when the buy-sell pressure is relatively balanced. The intensified covering of short-turnover is also accompanied by increased uncertainty and increased information asymmetry, suggesting that the buy decisions by short-sellers are likely to be informed.

To conclude, Chinese short-sellers trade on very short-term overpricing by short-selling in response to high contemporaneous return following low historical returns, and they cover the short positions after the overpricing is reversed. They believe that the past trend would continue, and the rebound following a downward trend should be temporal and would be reversed very soon. Short-sellers do not provide liquidity in buy-order imbalance. Intensified short-selling is accompanied by higher uncertainty and higher information asymmetry, suggesting either increased risk-bearing activities by short-sellers or private information possessed by short-sellers.

5.2. Trading strategies adopted by margin-traders

In this section, we continue to examine the trading motivations of margin-traders and propose several possibilities. First, margin-traders possess superior information or skill to identify undervalued stocks. Second, they provide liquidity by buying stock on margin in temporary sell-order imbalance. Third, they speculate in increased uncertainty. We examine these trading motivations using panel data by regressing daily margin-trading turnover on historical and contemporaneous returns.

We report the regression results in column (3) of Table 6. First, the coefficient on $r_{-5,-1}$

is indistinguishable from zero, indicating no significant relation between margin-trading and historical returns. The coefficient on r_t, however, is significantly negative, suggesting that margin-traders buy currently underperforming stock. These results suggest that margin-traders do not trade on momentum, but on temporal underpricing. Interestingly, we find intensified margin-trading in higher sell-order imbalance and attenuated margin-trading in higher buy-order imbalance. This is consistent with the liquidity provision hypothesis, and it might also suggest that margin-traders take the 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. Besides, intensified margin-trading is associated with higher spread, suggesting more informative trades by either margin-traders or their opposite sellers.

In column (4), we find no significant relation between the covering of margin-positions and $r_{-5,-1}$, but a marginally negative relation between the covering of margin positions and r_t. The evidence casts doubt on the underpricing hypothesis. If margin-traders buy to arbitrage away very short-term underpricing, we should observe intensified covering of margin positions following positive returns and therefore a positive coefficient on r_t, which is not supported by our results. We thus reject the hypothesis that margin traders trade to arbitrage away stock underpricing. If margin-traders buy to provide liquidity in sell-order imbalance, we should 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 suggests that, like the covering of short positions, the covering of margin positions intensifies on a day with relatively balanced buy-sell pressure. The support for the liquidity provision hypothesis is quite obscure.

We next explore whether the specious liquidity provision by margin-traders in sell-order imbalance is profitable. In unreported tests, we regress the day t 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 past five trading days. We find that intensified margin-trading activities tend to be followed by even higher sell-order imbalance and lower buy-order imbalance. This result remains 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 persistent: the correlation between order imbalance on day t and the average order imbalance in the past five days is 0.20, which is significantly positive. These results suggest that the strategy to provide liquidity by margin-traders is not profitable, as the sell-order imbalance does not subside immediately.

To sum up, Chinese margin-traders do not trade on momentum. They buy stocks with low contemporary returns, but we find no supporting evidence of their arbitrage against underpricing. They buy in strong selling pressure, but we find no sufficient evidence of intentional or profitable liquidity provision. Intensified margin-trading is associated with lower uncertainty and higher spread, as margin-traders trade opposite to other investors who are potentially informative.

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

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 while 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 that an upward (downward) trend is to begin and thus future returns should be higher (lower). In this section, we examine this return predictive power. Although we cannot match covering activities to the original positions, we can reasonably infer whether trades are profitable within a certain investment horizon.

Following Diether et al. (2009), we examine return predictability using panel data regression, with future abnormal returns with varying forecast horizons as the dependent variable. We skip one day to eliminate the impact of bid-ask bounce. The abnormal return is the daily return adjusted by the market model. We estimate the OLS market model using a rolling window of $[-396, -31]$ calendar days with a minimum of 180 trading days. The key explanatory variables are the daily short turnover ($Short_t$), margin turnover ($Margin_t$), covering turnover of short positions ($Cover_t^{Short}$), and covering turnover of margin positions ($Cover_t^{Margin}$). Reported control variables include the historical return cumulated in the past five trading days, the contemporaneous return, the contemporaneous spread, the contemporaneous buy/sell-order imbalance, and the contemporaneous intraday volatility. We also control for the average share turnover during the past five trading days, firm size, and book-to-market ratio.

Table 7 reports the regression results. Intensified short-selling turnover on day t is marginally associated with lower future returns on day $t + 2$, and intensified covering of short positions on day t is significantly associated with higher future returns on day $t + 2$. Intensified margin-trading and covering turnover, however, do not have significant predictive power for future returns. It indicates that short-sellers, on aggregate, are informative or skilled; margin-traders, however, do not possess superior information or skills. The predictive power of short-selling activity remains in one-week horizon, whereas the predictive power of covering of short positions remains even in 20 trading days. This evidence echoes the findings discussed in the previous sections. As the trades of short-sellers are informative, short-selling activities increase price efficiency (Tables 3 and 5). As margin-traders trade opposite to other potentially informative sellers (Table 6), their trades stabilize the market but do not contribute to improved price efficiency (Tables 3 and 5).

For the control variables, $r_{-5,-1}$ has a negative coefficient, and the explanatory power of the historical returns becomes stronger for a longer forecast horizon. The evidence indicates that returns in China tend to follow a short-term reversal. Higher *spread* predicts higher future return. Stronger buying pressure, however, predicts lower future return. Higher volatility predicts higher future return.

6. Further discussions

6.1. Technical indicators

Diether et al. (2009) report intensified short-selling activities following higher historical 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 trends and to design trading strategies in China. In this section, we explore whether technical indicators explain or predict the short-selling and margin-trading activities.

We first propose two cross-sectional technical indicators (Diether et al., 2009). On each day, we rank all shortable/marginable stocks by historical returns ($r_{-5,-1}$), and the dummy variable $winner_{-5,-1}$ ($loser_{-5,-1}$) equals one for stocks in the top (bottom) quintile and zero otherwise. Similarly, we rank stocks by contemporaneous returns (r_t) and define dummy variables $winner_t$ and $loser_t$. Besides, we identify four time-series technical indicators according to the moving average (MA) and trading range breakout (TRB) rules (Brock et al., 1992). The dummy variable $down^{MA}_{-1}$ equals one if the stock price on day $t-1$ drops and crosses over the past 20-trading days' moving average, which indicates an established short-term downward trend and is thus a sell signal, and zero otherwise. The dummy variable up^{MA}_{-1} equals one if the stock price on day $t-1$ rises and crosses over the 20-day moving average, which indicates a buy signal, and zero otherwise. The dummy variable $down^{TRB}_{-1}$ (up^{TRB}_{-1}) equals one if the stock price on day $t-1$ drops (rises) and penetrates the past 250-trading days' minimum (maximum) and zero otherwise. The breakout of the trading range indicates a long-term trend being established. Therefore, $down^{TRB}$ is a strong sell signal and up^{TRB} is a strong buy signal. We also define these four time-series indicators based on r_t. In sum, we use *loser* and *winner* dummy variables, two MA indicators, and two TRB indicators to predict or explain the trades of short-sellers and margin-traders. Control variables unreported for the sake of brevity include the lagged dependent variables, contemporaneous spread, contemporaneous sell/buy-order imbalance, contemporaneous intraday volatility, the average turnover ratio, sell/buy-order imbalance, and volatility during the past five trading days, firm size, and book-to-market ratio.

We report the regression results in Table 8. In Panel A, the explanatory variables are technical indicators defined based on historical returns. In Panel B, the explanatory variables are technical indicators defined based on contemporaneous returns. As shown in column (1) of Panel A, short-sellers favor stocks that are past losers and/or with a short-term downward trend. Besides, short-sellers avoid trading stocks with an established upward trend, either in the short run or in the long run. Column (1) of Panel B shows that short-sellers sell stocks that are currently winners and/or with a long-term downward trend. They avoid short-selling stocks that are currently losers with a new short-term trend, no matter upward or downward, and/or with a new long-term upward trend. Overall, short-sellers search for stocks with very short-term moderate overpricing following a well-established downward trend. The evidence suggests that technical analysis is indeed a helpful tool to predict and explain short-sellers' trading strategies.

In column (2), we regress the covering turnover of short positions on historical and contemporaneous technical indicators. Panel A shows that the coefficients on historical technical indicators are largely similar to those in column (1) except for r_t, indicating that the duration of short positions is likely to be quite short, and the covering decision is triggered mainly by the contemporaneous return. Panel B shows that the covering of short positions happens mostly for current losers, consistent with the results in Table 6 showing that short-sellers cover short positions after overpricing is corrected. The marginally positive coefficient on $winner_t$, however, might suggest forced closure of short positions to stop losses for cross-sectional winners. Negative coefficients on up_t^{MA} and up_t^{TRB}, however, indicate that when stock prices cross over the short-term MA or break out the 1-year maximum, losses incurred in short positions do not systematically result in forced closures of short positions.

Column (3) reveals that margin-traders rely less on technical analysis. None of the six dummy variables is significantly positive in Panel A, indicating that margin-traders do not trade on momentum, consistent with the results in Table 6. However, we can tell that margin-traders avoid trading stocks with short-term upward trend and/or long-term downward trend. Panel B shows that margin-traders favor current losers, which seems to support the underpricing hypothesis. Besides, they avoid trading stocks that are currently winners and/or with a long-term downward trend. However, column (4) of panel B further shows that margin-traders do not cover margin positions for contemporaneous winners or lowers. The coefficient on r_t is significantly negative in column (4) of panel A, suggesting attenuated covering of margin positions when return is higher. We thus find no supporting evidence that margin-traders cover the margin positions after underpricing is reversed. Based on these results, we can safely reject the underpricing hypothesis as an intentional trading motivation for margin-traders.

To sum up, we find evidence that Chinese short-sellers use technical analysis to select stocks and to time the market. Specifically, they short stocks with temporal overpricing, characterized by current winners following a downward trend. They cover short positions for stocks that are currently losers. Margin-traders, however, do not rely on technical analysis as much as short-sellers do. Margin-traders do not identify trends. Instead, they seem to capture very short-term underpricing implied by contemporaneous returns, and we find no evidence that they consistently do so in a rational way.

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

Who are these short-sellers and margin-traders? Are they retail investors, wealthy individuals, or institutions? We form our best conjecture on their identities based on 5-second transaction data from GTA. For records with non-zero trading volume, we calculate the average trade size in each 5-second interval as the dollar trading volume divided by the number of trades. 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 middle-size orders, and trades with an average dollar size greater than or equal to RMB 50,000 as large orders. We follow the buy/sell indicator provided by GTA to categorize trades to either buyer- or seller-initiated. As the data for the number of trades are available only for stocks traded on the Shenzhen exchange, the results in this section only cover a subsample of shortable/marginable stocks.

Panel A of Table 9 reports the summary statistics. Around 65% trades are middle-size orders, which contribute to 65% of the trade value. Although small orders contribute to around 30% of the trades, their value is no more than 10% of all trades. In contrast, although large orders contribute to only 6% of the trades, the value of these trades is around 27% of the aggregated trade value.

Panel B reports the relation between excess buy/sell and past/contemporaneous returns. We define daily excess large buying as *max[(large buy – large sell)/(large buy + large sell),0]*, adjusted by the average excess large buying of all available stocks on day t. Similarly, excess large selling is *max[(large sell – large buy)/(large buy + large sell),0]*, adjusted by its cross-sectional average. We define excess buying/selling from other investor groups in a similar way. In column (1) of panel B, we regress excess large buying on $r_{-5,-1}$ and r_t. The results show that large buy-orders increase as the historical return and contemporaneous return decrease, suggesting a contrarian strategy adopted by traders submitting large buy orders, who are arguably institutions or wealthy individuals. Column (2) shows no discernible relation between large sell-orders and returns. Column (3) reveals that either investors submitting middle-size orders trade on positive contemporary returns or their trades result in contemporary positive returns. Columns (4) and (6) suggest that traders submitting small and middle sell-orders are contrarian: they sell stocks with high historical returns. Column (5) shows no discernible relation between small buy-orders and returns. By comparing these results to Table 6, we conclude that the trading strategies of Chinese short-sellers or margin-traders are unique, as their trading patterns are not consistent with those of any typical investor groups identified in this section.

In panel C, we examine the interaction between short-sellers/margin-traders and other typical investor groups. For example, in the first row of panel C, we regress the daily short-selling turnover on excess buying/selling from large/middle/small investor groups. Note that the short volume is included in excess selling, 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 tend to submit large sell orders. The positive coefficient on middle buying and the negative coefficient on middle selling indicate that short-sellers trade opposite to investors who submit middle-size orders. The covering of short positions has a very noisy pattern, which increases in large sell-orders and decreases in middle buy- and sell-orders. In the third row, we find that the trading pattern of margin-traders is inconsistent with any typical investor group. Moreover, margin-traders trade opposite to investors who submit middle-size orders.

Finally, we regress future returns on trades from typical investor groups to examine whether the buying/selling by large/middle/small investors predict future returns. Panel D shows that on a one-day horizon, middle-size sell-orders erroneously predict future returns whereas small sell-orders correctly predict future returns. No trades have any predictive power for returns longer than one-week, with the exception of the marginal predictive power by middle buy-orders in the 20-day forecast horizon. In comparison, the trading activities by short-sellers correctly predict future returns, even in a 20-day horizon (Table 7).

To sum up, Chinese short-sellers and margin-traders are quite special investors. Their trading patterns do not replicate the strategies of any typical investor groups. Short-sellers and margin-traders trade opposite to the dominating forces in the market who submit middle-size orders, leading to lower return volatility (Tables 3 and 5). On an ex-post basis, investors submitting middle-size orders are not able to correctly predict future returns whereas short-sellers can.

6.3. Learning curve

An emerging market arguably has abundant profitable opportunities at the initiation of an influential reform process. Through a learning process, other investors can mimic the profitable trading strategies deployed by short-sellers and margin-traders. If short-seller's profits are a result of imitable skills, we expect to observe less predictive power of short-selling activities in the more recent period. If short-seller's profits are a result of very sophisticated skills or private information produced at a high cost, we will not see too many changes in the short-selling predictive power during this learning process.

We perform subsample analysis on return predictability and report the results in Table 10. Comparisons between panels A and B reveal that the predictive power of the covering turnover of short positions remains robust even in the recent subsample period. Actually, when we compare Table 10 with Table 7, the predictive power of short-selling is more pronounced in the recent subsample, suggesting that the trading strategies used by short-sellers are not imitable. Therefore, short-sellers' profits are likely to be driven by sophisticated skills or superior information.

6.4. Portfolio insurance

The increase in short-selling activity is likely to be driven by the increased scale of principal-guaranteed funds. We obtain the share of funds categorized as "principal-guaranteed" from WIND. We plot the aggregated fund share in billion RMB by month, as depicted by the gray bars in Figure 2. We also plot the aggregated monthly short-selling volume in million RMB using a solid line and the aggregated margin-trading volume in 10 million RMB using a dashed line. The margin-trading volume shows a clear upward trend, whereas the increase in short-selling volume is relatively depressed, particularly in 2012. The policy support tilted towards margin-trading in the refinancing pilot scheme implemented in August 2012 partially contributes to this trend.

Augmented Dicky Fuller test reveals that the unit root exists in these time-series. We thus calculate the monthly growth in fund shares and short volumes. Unreported results show that the correlation between short volume growth and fund shares growth is -4%, indistinguishable from zero. Consequently, portfolio insurance does not appear as a major trading motivation for short-selling. Besides, portfolio insurance requires traders to adjust positions in response to contemporaneous stock returns by buying winners and selling losers. This is unsupported by the evidence reported in column (1) of Table 6. Finally, the trading of index futures has been available since April 16, 2010. We argue that selling index futures is a cheaper and more convenient way than short-selling individual stocks to construct a hedging position for index funds. Therefore, portfolio insurance is not a major motivation for short-selling.

6.5. Index future

The initiation of index futures trading was another influential reform during the sample period. CSRC announced the plan for index future trading on February 20, 2010, and the trades began on April 16, 2010, which is 11 trading days after the initiation of short-selling and margin-trading on March 31, 2010. This event might influence our results in two aspects.

First, trading of index future partly contaminates the event day returns shown in Figure 1 and Table 2. However, only the 90 events in the first batch are influenced. We thus perform robustness test by examining the event day returns of the second batch and the results are qualitatively unchanged. The trading of index future, therefore, does not entirely drive the negative returns upon the lifting of bans on short-selling and margin-trading.

Second, trading of index future partly contaminates the comparison results reported in Table 3. We thus perform robustness check by examining the changes in efficiency measures and return distributions for stocks added to the list in the second batch. The results are qualitatively unchanged. Therefore, the trading of index future cannot fully account for the improved efficiency and reduced volatility after short-selling and margin-trading are allowed.

6.6. Information, or price manipulation?

In section 5.3 we show that the trades by short-sellers are able to predict future stock returns. Readers might suspect that short-sellers intentionally manipulate the market, leading to the observed return predictability. We rule out this alternative explanation according to two pieces of evidence. First, Table 4 shows that although short-selling is becoming popular, short-selling contributes to only 0.73% of total trading volume. Given such low short-selling volume, it is dubious that short-sellers have the power to manipulate the market. Second, column (1) of Table 6 shows that intensified short-selling turnover is associated with reduced sell-order imbalance, and column (2) shows that intensified covering of short positions is associated with reduced buy- and sell-order imbalance. If trading by short-sellers predict future returns due to price manipulation, their sales (purchases) should be accompanied by greater sell- (buy-) order imbalance, which is not supported by the empirical evidence. In sum, we argue that the return predictability by short-sellers is not driven by price manipulation.

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 improved price efficiency and lower return 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 return volatility. Fourth, we find intensified short-selling in response to higher contemporaneous return and following lower historical return, suggesting that short-sellers arbitrage away temporal overpricing. Return predictability tests reveal that the trades by short-sellers predict future returns, indicating that short-sellers are informed traders. Finally, short-sellers and margin-traders are not market destabilizers. By trading opposite to other investors groups, short-selling and margin-trading effectively reduce return volatility.

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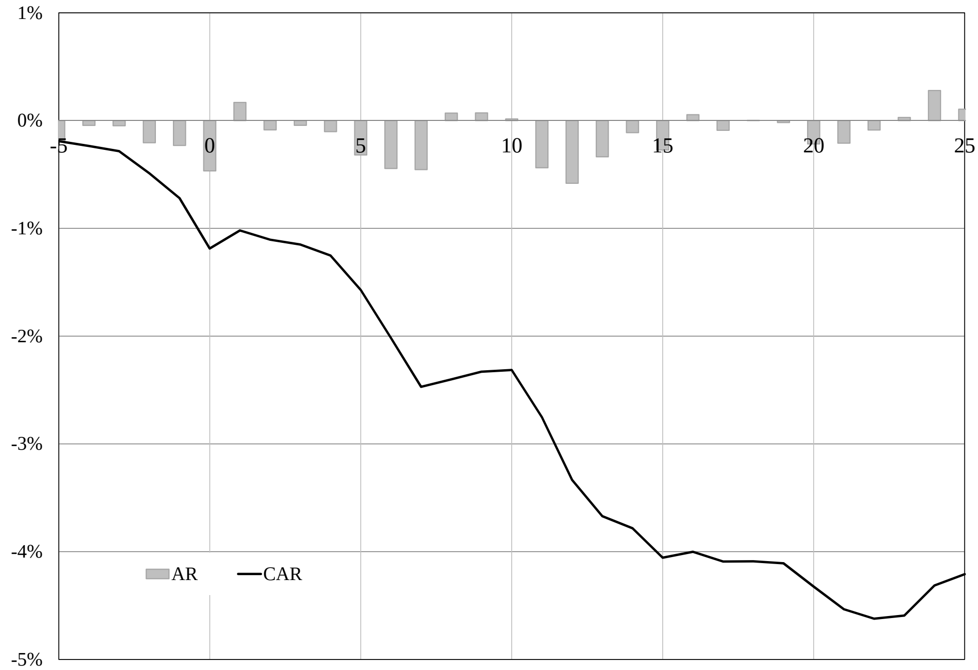

Figure 1: **Abnormal returns and cumulative abnormal returns around additions**
This figure plots the abnormal returns and cumulative abnormal returns around addition events. The horizontal axis shows the event time in trading days relative to the addition event. An addition event is defined as one in 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 using grey bars and the cumulative abnormal returns using a line. The abnormal return is the daily return adjusted by 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.

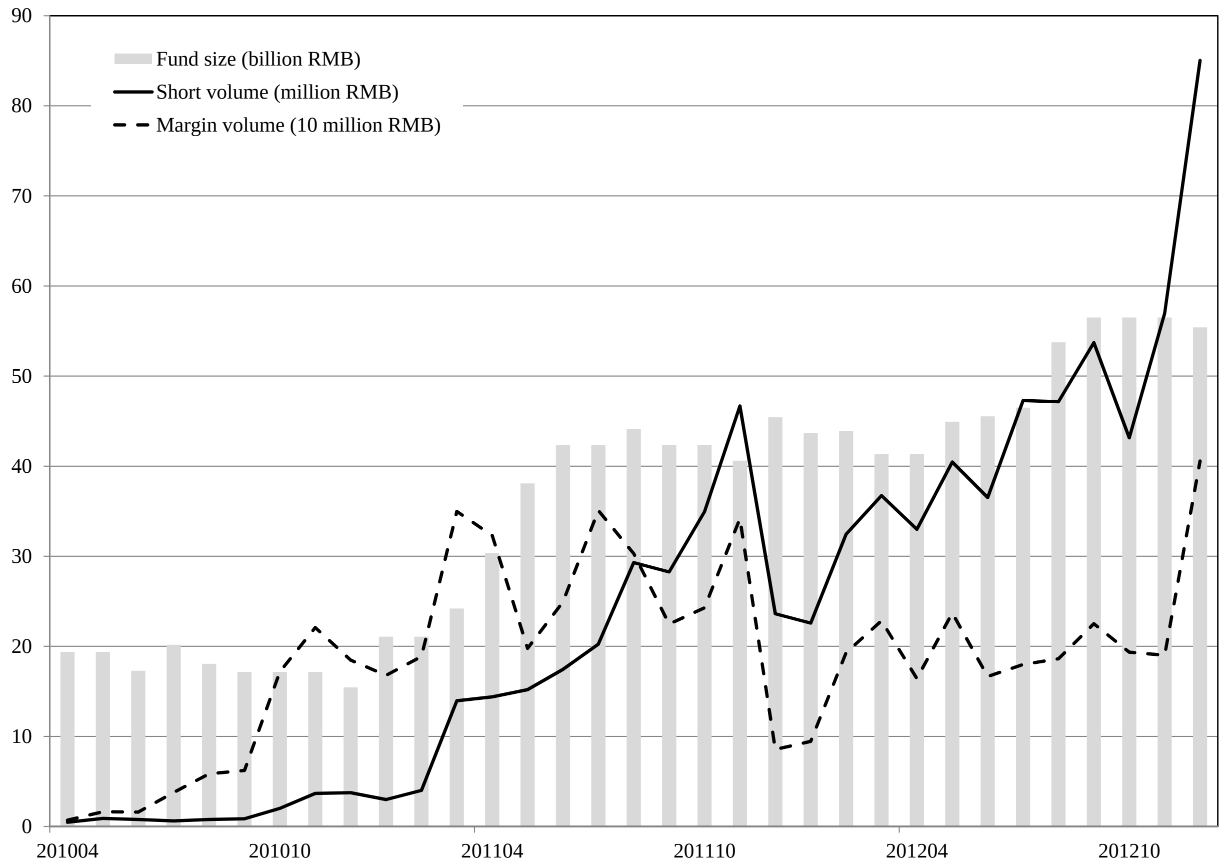

Figure 2: **The scale of principal-guaranteed fund**
We plot the book value of principal-guaranteed fund (in billion RMB) dipicted using the gray bar along the calendar time. We also plot the monthly trading volume of short-selling (in million RMB) using a solid line and the margin-trading volume (in 10 million RMB) using a 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 that are more than three standard deviations away from 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 that are more than three standard deviations away from 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 stock 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 the sake of brevity include log firm size, annualized share turnover, dummy variables for dual-listed A-H stocks and A-B stocks. We winsorize variables at the 1st and 99th 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_+	$\|\rho_-\|$	$\|\rho_+\|$	$\|VR\|$
$Short$	-4.806**	0.073	-2.388	-2.175**	-1.369
	(2.25)	(0.04)	(0.83)	(2.02)	(0.75)
$Cover^{Short}$	-37.887	1.565	5.041	-33.305***	6.818
	(1.43)	(0.11)	(0.43)	(8.49)	(0.76)
$Margin$	-1.608	0.074	-0.973**	-0.900*	-1.393*
	(1.37)	(0.11)	(2.43)	(1.73)	(1.85)
$Cover^{Margin}$	3.883**	4.581***	-0.485	0.402**	-2.455
	(2.30)	(3.39)	(0.17)	(2.23)	(1.08)
N	457	457	457	457	457
$R^2 - adj$	15.5%	1.8%	15.9%	14.0%	9.6%
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 returns and other determinants using panel data. The turnovers are the respective trading volume in shares scaled by the daily total trading volume $\times 100$. $r_{-5,-1}$ is the cumulative stock return in the past five trading days, and r_t is the contemporaneous stock return. $oimb_t$ is contemporaneous daily stock-level order imbalance, which is volume of buys minus sells scaled by the total volume of buys and sells. We follow the buy/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 the difference in the daily high and low price divided by the high price. $spread_t$ is the volume-weighted effective spread on day t. Other control variables unreported for the sake of brevity include the lagged dependent variable, log firm size, book-to-market ratio, the historical share turnover averaged in the past five trading days, the historical sell- and buy-order imbalance, and the historical σ. In columns (2) and (4), we control for the lagged short turnover and margin turnover, respectively. We winsorize variables at the 1st and 99th percentile. The standard errors are clustered by calendar date and stock. We report t-statistics 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)
$r_{-5,-1}$	-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)
$oimb_t^-$	-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)
$spread_t$	0.002***	0.003***	0.007**	0.003
	(3.60)	(4.40)	(2.14)	(1.08)
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 $[-396, -31]$ calendar days with minimum of 180 trading days. $Short$, $Cover^{Short}$, $Margin$, and $Cover^{Margin}$ are the short-selling turnover, the covering turnover of short positions, the margin-trading turnover, and the covering turnover of margin positions, respectively. 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 volume-weighted effective 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 the difference in the daily high and low price divided by the high price. Other control variables unreported for the sake of 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. We report t-statistics 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 the sake of brevity include the lagged dependent variable, the contemporaneous effective 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 the 1st and 99th percentile. The standard errors are clustered by calendar date and stock. We report t-statistics 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				
$loser_{-5,-1}$	0.019***	0.014**	0.035	0.050*
	(2.61)	(2.19)	(1.31)	(1.85)
$winner_{-5,-1}$	0.001	0.003	0.022	0.049*
	(0.13)	(0.44)	(0.84)	(1.67)
$down_{-1}^{MA}$	0.063***	0.042***	-0.038	-0.095*
	(4.02)	(3.38)	(0.54)	(1.90)
up_{-1}^{MA}	-0.094***	-0.070***	-0.113**	-0.048
	(7.50)	(5.51)	(2.22)	(0.99)
$down_{-1}^{TRB}$	0.019	0.011	-0.136**	-0.042
	(1.08)	(0.75)	(2.46)	(0.67)
up_{-1}^{TRB}	-0.107***	-0.059	0.058	-0.069
	(3.11)	(1.57)	(0.42)	(0.71)
r_t	0.900***	-1.275***	-5.781***	-1.669**
	(3.38)	(5.11)	(6.42)	(1.99)
N	65,371	65,341	65,371	65,362
$R^2 - adj$	52.3%	57.1%	46.4%	50.9%
Panel B: Regressing on contemporaneous technical indicators				
$r_{-5,-1}$	-0.286***	-0.252***	-0.159	0.155
	(3.79)	(3.31)	(0.62)	(0.60)
$loser_t$	-0.053***	0.017***	0.232***	-0.151***
	(6.06)	(2.65)	(7.04)	(4.97)
$winner_t$	0.175***	0.017*	-0.412***	-0.115***
	(15.29)	(1.71)	(10.79)	(3.76)
$down_t^{MA}$	-0.033***	0.011	0.092	0.079
	(3.08)	(0.96)	(1.37)	(1.29)
up_t^{MA}	-0.036**	-0.069***	-0.084	0.056
	(2.15)	(4.62)	(1.43)	(1.17)
$down_t^{TRB}$	0.053***	-0.015	-0.212***	0.075
	(3.30)	(1.11)	(3.82)	(0.97)
up_t^{TRB}	-0.122***	-0.129***	0.140	-0.081
	(5.10)	(3.37)	(0.96)	(0.89)
N	65,371	65,341	65,371	65,362
$R^2 - adj$	53.0%	57.0%	46.6%	50.9%

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 the sake of brevity include past order imbalance $oimb_{-5,-1}$, effective 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 the sake of 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 the sake of brevity include $r_{-5,-1}$, r_t, σ_t, and $tv_{-5,-1}$. We winsorize variables at the 1st and 99th percentile. The standard errors are clustered by calendar date and by stock. We report t-statistics 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-buying/selling by investor groups on past and contemporaneous returns						
$r_{-5,-1}$	-0.036**	0.003	0.014	0.023**	-0.002	0.025**
	(2.11)	(0.16)	(1.01)	(1.99)	(0.20)	(2.49)
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 buying/selling						
$Short_t$	0.041	0.132***	0.578***	-0.245***	0.068	-0.018
	(0.85)	(2.67)	(6.84)	(3.88)	(0.72)	(0.23)
$Cover_t^{Short}$	0.063	0.092**	-0.122*	-0.097*	0.046	-0.048
	(1.64)	(2.17)	(1.84)	(1.92)	(0.55)	(0.60)
$Margin_t$	0.276	-0.017	-2.371***	0.679**	-0.089	0.006
	(1.37)	(0.10)	(8.72)	(2.53)	(0.26)	(0.02)
$Cover_t^{Margin}$	0.035	0.210	-0.524***	-1.195***	-0.242	-0.132
	(0.17)	(1.09)	(2.66)	(3.98)	(0.66)	(0.34)
CAR_{+2}	0.107	0.045	0.068	0.302*	-0.114	-0.441***
	(1.19)	(0.46)	(0.37)	(1.83)	(0.66)	(2.75)
$CAR_{+2,+5}$	0.164	0.396	0.282	0.621	0.280	-0.114
	(0.73)	(1.63)	(0.78)	(1.52)	(0.58)	(0.29)
$CAR_{+2,+10}$	0.165	0.468	0.730	0.529	0.356	-0.545
	(0.51)	(1.31)	(1.29)	(0.85)	(0.49)	(0.86)
$CAR_{+2,+20}$	-0.042	0.223	1.629*	1.282	0.239	0.942
	(0.09)	(0.36)	(1.87)	(1.25)	(0.20)	(0.88)

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 the sake of 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%