Costly and unprofitable speculation: Evidence from trend-chasing Chinese short-sellers and margin-traders ☆

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Keywords: Short selling, margin trading, efficiency, stabilization, speculation

JEL classification: G12, G14, G15, G18

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August 24, 2012

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1. Introduction

The impact of short-sale constraints on the capital market has been highly controversial. There is intense debate over whether the constraint induces upward bias in asset prices, reduces pricing efficiency, and helps to stabilize the market at all (Miller, 1977; Diamond and Verrecchia, 1987; Hong and Stein, 2003). Since U.S. Securities and Exchange Commission temporarily banned short sales in September 2008, benefits and costs of this ban had faced more stringent scrutiny. France, Spain, Italy and Belgium imposed similar ban in August 2011 despite of the hot debate over the real function of short-sale constraints. On the other hand, the discussions concerning margin requirements have attracted the attention of government, investment public, and academia since the market crash on October 1987. Margin traders, as potentially informative speculators, are blamed for producing excess volatility and destabilizing the market. Chowdhry and Nanda (1998), however, argue that the margin requirement itself brings about additional uncertainty and contributes to market destabilization.

Whereas western developed markets impose more stringent constraints on short-selling and margin-trading, China launched its long-awaited pilot scheme on March 31 2010, allowing 90 constituent stocks on a designated list to be sold short and purchased on margin. This list was revised twice in 2010, and expanded to include 280 constituent stocks and 7 exchange-traded-funds (ETF) in December 2011. China Securities Regulatory Committee (CSRC) then announced the successful completion of the 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 (Chang et al., 2007; Bris et al., 2007; Diether et al., 2009a,b). First, the constraints are removed for groups of stocks overnight. We test whether short-sale constraints contribute to stock overvaluation by examining the event returns. Second, we explore the influence of constraints on the pricing efficiency by comparing R^2 and cross-autocorrelation before and after the event. Third, we compare liquidity, volatility and price informativeness before and after the event. Fourth, China makes the *daily* short, margin, and associated covering *volume* publicly available at the stock level, providing a rare opportunity to examine the trading behaviors of short-sellers and margin-traders. U.S. researchers, in comparison, usually only observe the *monthly* short *interest*. We analyze the relation between investors' trading activity and stocks' past return and future returns. Such an investigation enables us to infer the trading motivations and assess the profitability of Chinese short-sellers and margin-traders.

Our main results are summarized as follows. 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 removed. We find that addition to the designated list is associated with an average abnormal return of -44.5 bps, which is significantly different from zero. The cumulated abnormal returns around the event remain negative for 60-trading days after the event. The evidence strongly supports the conjecture that short-sale constraint contributes to stock overvaluation (Miller, 1977).

Then, we obtain the daily returns during the half-year period before and after the event and calculate the distributions of daily abnormal returns. We find higher return volatility after removal of the bans. At this stage, we cannot tell whether it is short-selling or margin-trading that contributes to increased volatility. Nevertheless, consistent with the risk-expected return relationship, the return is on average higher after removal of the bans. The skewness is less positive, consistent with the market-stabilization function of short-sale constraint proposed by Xu (2007). The probability for extremely negative return to occur becomes higher, somehow supporting the traditional wisdom that short-sellers and margin-traders destabilize the market. We calculate alternative volatility measures such as intra-day price range and semivariance conditioning on positive or negative returns. Consistently, we find wider price range and higher variance after removal of the bans. In addition, semivariance increases significantly in the up-market, but not in the down-market.

For the efficiency test, we estimate the market model based on daily returns during the period of half-year before and after the events, conditioning on negative or positive market returns. We find higher betas in both up- and down-market, indicating higher sensitivity to the market-wide information after removal of bans. Furthermore, we discover significant increase in the up-market R^2, but no discernible change in the down-market R^2. This indicates lower pricing efficiency in the up-market after removal of the bans, since higher R^2 indicates less firm-specific information reflected in price and hence lower efficiency. As an alternative measure of efficiency, we calculate the cross-autocorrelation ρ between stock return and the lagged market return, which measures the price delay. We find significantly higher ρ in the up-market, but no discernible change in the down-market. Therefore, price delay increases and hence efficiency drops in the up-market, not in the down-market, completely consistent with the R^2 comparison results.

We obtain transaction data during 90-days before and after the event to calculate measures of liquidity. We find that the percentage quoted spread, effective spread, and realized spread all increase after removal of the bans. Besides, probability of informed trading (PIN) is no higher for stocks listed on Shenzhen exchange. This evidence does not support Sharif et al.'s (2012a) conjecture that uninformed noise-traders are intimidated by potentially informative short-sellers and/or margin-traders, leading to deteriorated liquidity.

Next, we utilize the panel data of daily short-selling, margin-trading, and associated covering activities at stock level to examine the trading motivations and assess the profitability of Chinese short-sellers and margin-traders. We investigate four possible trading motivations for Chinese short-sellers (Diether et al., 2009b). First, we examine whether they possess superior information or skills in identifying overvalued stocks as U.S. investors do. Surprisingly, we find a negative relation between past return and short volume, indicating intensified short-selling activity following lower past return. It suggests that Chinese short-sellers do not identify overvaluation. Instead, they are trend-chasers. Second, we examine the skills that they possess. Motivated by their trend-chasing behaviors, we identify four technical indicators (Brock et al., 1992): a buy (sell) signal generated by crossing-over the 20-day moving average from below (above), and a probable buy (sell) signal generated by breaking out the trading range defined by the past 250-day maximum (minimum). Together with $Winner$ ($Loser$) indicator for top (bottom) quintile stocks, we examine whether short-sellers rely on technical analysis at all, and empirical results strongly suggest that they do so. We observe intensified short-selling activity after stock price drops below the 20-day moving average and/or the stock return is among the bottom quintile on the previous day. Besides, we observe reduced short-selling activity after stock price rises above the 20-day moving average, breaks out the 250-day minimum, and/or stock return ranks in the top quintile on the previous day. It seems that cross-over of short-term moving average, $Winner$ and $Loser$ are interpreted as trend signals. The trading-range breakout, however, is interpreted as a reversal signal. Third, we observe intensified short-selling activity in high volatility and low spread. This supports short-sellers' speculating behavioral in divergence of opinions, since divergence of opinions leads to competitive orders and therefore low spread. Intensified short activity is followed by widening spread, suggesting converging opinions thereafter. Fourth, we observe intensified short-selling activity coinciding with greater buy-order imbalance, seemingly consistent with the liquidity provision hypothesis. However, the covering of short position is unrelated to order imbalance at all. Using ex-post data, intensified short activity is not followed by immediate reversal of buy-order imbalance. These pieces of evidence hint that short-selling in buy-order imbalance in not intended to provide liquidity, and this action is not immediately profitable.

Similarly, we analyze the possible trading motivations by margin-traders. The positive relation between past return and margin volume reveals that margin-traders do not identify undervaluation either, but chase the trend. They also rely on technical analysis, and interpret technical indicators in a way similar to short-sellers. Besides, we observe intensified margin-trading that coincides with low volatility and is followed by high volatility, supporting the "destabilizing" function of margin-trading. We observe no discernible relation between margin-trading and order imbalance, and hence no support to liquidity provision hypothesis.

As an overall assessment of profitability, we investigate whether short-selling and margin-trading activities predict future returns. Surprisingly, we find that they incorrectly predict the future. Cross-sectionally, intensified short activity is followed by higher return, whereas intensified margin-trading is followed by lower return. The strategy to long the heavily-shorted stocks and short the slightly-shorted stocks produces a daily abnormal return of 30.7 bps. The strategy to long the slighted-margined stocks and short the heavily-margined stocks produces a daily abnormal return of 8.2 bps. Therefore, the hypothesis of superior information or skills is refutable.

To sum up, Chinese short-sellers or margin-traders do not possess superior information or skill. They do not identify mispricing in the market. They rely heavily on technical analysis, which may be uninformative by itself, or interpreted in a wrong way, to identify the trend and chase it. They short-sell in high order imbalance, which is not intended to provide liquidity. So far we conjecture that speculation is the only reasonable trading motivation by Chinese short-sellers and margin-traders, which is not profitable at all.

Finally, echoing the comparison of volatility and efficiency before and after removal of the bans, we examine the cross-sectional relation between trading activity and volatility/efficiency. Consistent with prior results, we find no evidence that short-selling adds to volatility. Instead, intensified margin-trading and associated covering are followed by increased volatility, especially in the up-market. However, it is the short-selling activity, not margin-trading, that reduces efficiency in both the down- and up-market. In short, margin-traders destabilize the market. Short-sellers, by speculating on the position opposite to potentially "correct" traders, do not produce excess volatility but reduce efficiency.

This study contributes to the literature in several aspects. First, we add more evidence to the literature concerning the impact of constraints on short-selling and margin-trading. Second, we are the first to examine comprehensively the change in valuation level, return volatility, skewness, market efficiency, and liquidity after removal of the bans on short-selling and margin-tradings in the Chinese market. Third, we are the first to infer possible trading strategies of Chinese short-sellers and margin-traders and assess their profitability by utilizing the daily short/margin volume available in China. This study potentially helps market participants to understand why, when, and how Chinese short-sellers and margin-traders trade and most importantly, how to improve their trading strategies. The implication sheds light on regulation and investment strategies in other developing and developed markets. Finally, Chinese capital market experienced burgeoning growth in the last two decades, and it is now one of the most important financial markets in the world. There are arguably more chances of market inefficiency and accompanied trading opportunities at the beginning of an economic reform. The trading patterns documented in this paper are reminiscent of the lousy Chinese warrant market in 2005-2008 (Xiong and Yu, 2011). It is thus illuminating to investigate this huge developing market and provide investment suggestions to domestic and foreign investors.

2. Literature review

An investor buy a stock if she has a piece of good news about the underlying firm. If the news is extraordinary positive with high precision, she may build up a leveraged position by borrowing from the broker (margin-trading) or from other resources. However, she meet with difficulties in selling the stock short if she have a piece of bad news. Short-selling, the trading activity to sell a stock without owning it, may be prohibited by law in certain countries, not practiced due to lack of lender of stocks, too expensive in terms of loan fees, or inapplicable 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, asset valuation, efficiency, and market stabilization

Miller's (1977) seminal model predicts overvaluation associated with short-sale constraint, since pessimistic investors who do not originally own the stock are prevented from trading. In contrast, Diamond and Verrecchia (1987) predict no overvaluation since investors already account for this constraint in a rational-expectation framework. Empirical studies generally support the overvaluation view (see, e.g., Autore et al., 2011; Chang et al., 2007; Chen et al., 2002; Geczy et al., 2002; Jones and Lamont, 2002; Nagel, 2005). Among them, Chang et al. (2007) take advantage of the unique institutional setting in Hong Kong, in which only stocks on a pilot list can be sold short. Since the list was routinely revised at around quarterly frequency, a series of events are identified in which short-selling constraint is removed or imposed overnight. The authors find negative returns around the events when the short-sale ban is removed, strongly supporting Miller's (1977) overvaluation hypothesis.

Another stream of literature studies the impact of short-sale constraints on pricing efficiency. Diamond and Verrecchia (1987) predict that short-sale constraint hinders price discovery, especially for negative information. Bris et al. (2007) provide supporting evidence from an international comparison between markets with different institutional settings concerning short-sale constraint. The authors separately estimate the market model conditioning on positive or negative market returns, and use the down- minus up-market R^2 to measure the efficiency loss induced by short-sale constraint. Besides, the authors calculate the cross-autocorrelation between stock return and lagged market returns, conditioning on positive or negative lagged market returns, and use the down- minus up-market cross-autocorrelation to measure the price delay because of short-sale constraint. Over all, the authors find that in countries where short sales are allowed and practiced, prices incorporate negative information faster, supporting Diamond and Verrecchia (1987). In the same spirit, Saffi and Sigurdsson (2011) analyze the proprietary data about daily stock lending and loan fee from 26 countries and calculate similar cross-autocorrelation to measure efficiency, finding lower efficiency for stocks with more binding short-sale constraint. Chen and Rhee (2010) document supporting evidence that the speed of price adjustment is faster for shortable stocks than for non-shortable stocks in Hong Kong.

There are also hot debate over whether short-sale constraint helps to stabilize the market at all. Several studies cast doubt on this stabilization function. For example, based on slow adjustment to negative news, Diamond and Verrecchia (1987) predict more negatively skewed returns associated with short-sale constraint. Similarly, Hong and Stein's (2003) model suggests that, due to 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. Besides, the return is predicted to be more negatively skewed when short-sale constraint is binding. However, in supportive of the market stabilization role, 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 short-sale constraints. Empirical studies such as Bris et al. (2007) find that in countries where short-sale is not allowed or practiced, stock return is less negatively skewed, supporting Xu (2007) and the stabilization function played by short-sale constraint, although the frequency for extremely negative return to occur is no lower. Consistently, Chang et al. (2007) document more positively skewed returns and lower frequency of extremely negative returns under short-sale constraint in Hong Kong. Saffi and Sigurdsson (2011) report additional evidence that more binding short-sale constraint, measured by less lending supply, is associated with more positive skewness, higher kurtosis, but no more extremely negative returns or higher price instability/downside risk.

Since the disastrous 2007-09 crisis and consequent U.S. short-sale ban in September 2009, the market stabilization function of short-sale constraint has been even more contentious. According to SEC Chairman Christopher Cox, "the emergency order temporarily banning short selling of financial stocks will restore equilibrium to markets." The ban was imposed in France, Belgium, Italy and Spain in 2011 as well. Although this ban was intended to stabilize the turbulent capital market in 2008, Boehmer et al. (2011) find that it failed to support price. Furthermore, the ban ruins liquidity, slows down price discovery (Beber and Pagano, 2012; Marsh and Payne, 2012), and substantially increases the market making costs in the options market (Battalio and Schultz, 2011).

2.2. Short-selling activity and returns

In spite of ample vivid stories concerning what ‘‘evil” short-sellers have done in the long finance history (Bris et al., 2007), there is still hot debate over the relation between short-selling activities and prior/subsequent returns. Neither do we thoroughly know about short-seller's trading motivation, strategy, or profitability. Data is the most important limitation. The commonly used data in U.S. is the monthly short-selling interest (Figlewski, 1981; Safieddine and Wilhelm, 1996; Karpoff and Lou, 2010; Hirshleifer et al., 2011, among others). For example, Figlewski (1981) finds that stocks with higher monthly short interest have lower subsequent returns. The author argues the short interest to proxy for the volume if the constraint does not exist. Therefore, higher short-interest indicates more negative information not incorporate into stock price, which is eventually diffused and leads to price drops. Different from short volume, which is the number of shares sold short during the period, short interest is the open short positions that is not covered at the end of the period.

A rare intra-day short-selling transaction data was available in U.S. from January 1 2005 to August 6, 2007, due to the implementation of regulated SHO pilot scheme (Diether et al., 2009a,b; Henry and Koski, 2010). This precious data, however, is no longer updated since the scheme terminated by 2007. Some researchers are able to obtain proprietary data at daily or transaction level, even with some clues to the identity of traders (Cohen et al., 2007; Geczy et al., 2002; D'Avolio, 2002; Boehmer et al., 2008). However, the proprietary data is not publicly available for replications in other studies.

Diether et al. (2009b) investigate the short-term relation between short-selling activities and returns using regulated SHO data at transaction level. Short-sellers are found to short sell more following positive returns and before negative returns, and short-selling activities positively predict future returns over the five-trading day horizon. Similarly, Boehmer et al. (2008) utilize proprietary order data and find that heavily shorted stocks underperform slightly-shorted stocks by 1.16% over the next 20 trading days. Cohen et al. (2007), using proprietary data concerning the loan fees and the amount of stock lending, find that higher short-demand is associated with more negative return in the following month. Takahashi (2010) use Japanese stock lending data and find that the most heavily-shorted stocks underperform least heavily-shorted stocks up to three months.

Why short sellers are able to predict future returns? Diether et al. (2009b) propose four alternative explanations. First, short-sellers may possess inside information, especially negative private information. Several studies support this view (Anderson et al., 2012; Boehmer et al., 2008; Christophe et al., 2004, 2010; Karpoff and Lou, 2010). For example, Karpoff and Lou (2010) document increased short-sales at least one year before financial misconduct is publicly revealed. Second, short-sellers are likely to be sophisticated investors, who are more capable in identifying overpriced securities. In supportive of this view, Boehmer et al. (2008) report that 74% of short-selling orders are executed by institutions, and less than 2% are submitted by individual investors. Third, short-sellers may voluntarily provide liquidity by short-selling in temporary buying-order imbalance. After this order imbalance subsides, price drops back to fundamental value. Short-sellers then cover the short position and make profit. This hypothesis predicts higher short volume coinciding with increased buy-order imbalance and higher covering volume coinciding with reduced buy-order imbalance. For this strategy to be profitable, higher short volume should be associated with reduced buy-order imbalance in the future. Fourth, short-sellers may be speculators in high uncertainty. If high uncertainty comes from information asymmetry, more short-selling should coincide with high bid-ask spread, which falls after the information gets public. If high uncertainty comes from divergent opinions, more short-selling should coincide with lower spread because of competitive orders, and the spread widens after opinions converge. Different from the first three trading motivations, speculation does not guarantee any profit.

In the present study, we use the Chinese daily short-selling volume and covering of short positions at the stock level to investigate the relation between short-selling activity and returns. As one of the most important developing security markets in the world, Chinese investors are known for "irrationality". We are thus curious to know the nature of Chinese short-sellers, their trading strategy, whether they are profitable, and whether they leads to more volatility, higher efficiency, etc. This study is complementary to Sharif et al. (2012a,b). Sharif et al. (2012b) investigate the market reaction to the event of 90 stocks added to the designated list in March 2010 as the first batch in China. They find negative abnormal returns on both announcement days and effectives day, supporting Miller's (1977) overvaluation story. Besides, they find lower trading volume following removal of the bans, and propose a possible explanation that uninformed investors choose not to participate to avoid trading against informative short-sellers, leading to reduced market quality. Sharif et al. (2012a) find increased quoted spread after removal of bans for the 90 stocks, consistent with the non-participation story by uninformed investors.

2.3. Margin trading

Margin-trading allows investor to construct a leveraged long position through borrowing from registered security company. Both short-selling and margin-trading were strictly prohibited in China before March 2010. However, we argue that the ban on margin-trading is less binding, as investors could circumvent the constraint by borrowing from various other resources and home-make similar margin positions. In addition, if a sufficient number of investors participate in the market, the ban on margin-trading does not hinder the discovery of positive information. Bans on margin-trading become binding given a limited number of participants who are financially constrained.

Traditional wisdom suggests that margin-traders, as speculators, trade to destabilize the market, especially after the market crash in October 1987. Therefore, regulatory bodies tend to propose more stringent margin requirement to intimidate speculators. Chowdhry and Nanda (1998), however, develop a model predicting increased market instability brought by the margin requirement itself. The intuition is consistent with models proposed by Gârleanu and Pedersen (2011), Xiong (2001), and Yuan (2005). Empirical studies fail to support those models. For example, Hardouvelis and Peristiani (1992) examine the stock return and volatility after margin requirement changes in Japan. They find that after higher margin requirement is implemented, returns tend to be lower for marginable stocks, but not for non-marginable stocks. Besides, after higher margin requirement is implemented, the realized volatility drops substantially for marginable stocks and not for non-marginable stocks. Hence, the results seem to support the view that higher margin deter destabilizing speculators in Japan and does not add into additional market instability. Seguin (1990) investigates the inception of margin-tradings of OTC stocks. He finds positive event returns, no higher volatility, and improved liquidity and price informativeness. Hirose et al. (2009) examine the weekly data from Japanese margin trading and short-selling activities. Interestingly, the authors find that although margin-trading is dominated by retail investors in Japan, who are presumably uninformed, their margin-trading activities positively predict future returns, especially for small firms.

3. Institutional background

Short-selling or margin-trading had been prohibited in the Chinese security market (Bris et al., 2007) before a pilot scheme was implemented in March 2010. Table 1 shows some information related to the timeline of this influential reform. On March 31, 2010, two major exchanges of mainland China allowed ‘‘qualified” investors to buy eligible stocks on margin or short sell those stocks under a pilot scheme. In total, 90 constituent stocks of 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 minorly revised twice in 2010, with six stocks deleted from the list, and six new stocks added to the list, and the total number of eligible stocks remained 90. On December 5, 2011, the list was substantially expanded to include 280 constituent stocks of the SSE 180 Index and SZSE 100 Index, as well as 7 exchange-traded-fund (ETF). CSRC then announced that the pilot scheme was turned to a routine practice and accordingly revised the detailed implementation rules, stipulating more specific margin requirements.

Stocks and ETF shall meet several criteria to be eligible for short-selling and margin-trading. According to the implementation rules promulgated by Shanghai exchange, eligible stocks shall satisfy size, liquidity, and volatility requirements. [1] According to the administrative rules promulgated by CSRC, only "qualified" investors can buy stocks on margin or sell stocks short. The requirements for membership qualification may differ across security companies. [2] It seems that, like Japan and Taiwan, short-selling and margin-trading business are catering retail investors, not institutions. The uptick rule has been strictly implemented, prohibiting short-selling at a price below the previous transaction price. Naked short-selling is strictly prohibited.

The cost of short-selling and margin-trading is extraordinarily high. For example, Haitong Securities charge the same fee for security lending and margin trading for all stocks: 3% above the prime rate for 6-month loans, since the maximum opening period for short- or margin-position is 6 months as stipulated by CSRC. On July 6, 2012, the prime rate for 6-month loan (published by The People's Bank of China) was 5.60%. Thus, Haitong charged 8.60% interest rate for margin-trading and stock-lending. Huatai Securities, however, charged 8.60% for margin trading and 10.60% for security lending. In comparison, D'Avolio (2002) report that the value-weighted loan fee of a sample portfolio is only .25%, and only 9% of stocks have loan fee above 1%. Even stocks with high loan fees have a mean fee of 4.3%.

The investor who buys stocks on margin and short-sell stocks has to keep the account

[1] Source: http://www.sse.com.cn/cs/zhs/xxfw/flgz/rules/sserules/sseruler20111125b.html. First, to be eligible for margin-trading, the firm should have no less than 100 million trader shares and no less than RMB 500 million (US$79 million) public float. To be eligible for short-selling, the firm should have no less than 200 million tradable shares and no less than RMB 800 million (US$126 million) public float. Second, the number of shareholders is no less than 4,000. Third, in any given day during the past three months on a rolling basis, the daily turnover is no lower than 15% of index turnover, the daily trading value is no lower than RMB 50 million (US$7.89 million), its average return does not deviate more than 4% from index return, and its return volatility is no higher than 5 times of index volatility. The middle exchange rate published by The People's Bank of China was 6.3355 RMB/US$ on May 31, 2012.

[2] Taking the guidance of Haitong Securities for an example, investors must satisfy below requirements to be qualified for margin purchase and short-sell. First, the investor has a trading history longer than one and a half years with this security company (reduced to half a year after December 2011), with capital amount no lower than RMB 500,000 (approximately US$ 78,500). The investor need to demonstrate the basic knowledge by passing a professional knowledge exam and a risk-attitude test. Other qualitative requirements include good trading record, low bankruptcy risk, non-corporate insider, etc. Source: http://www.htsec.com/htsec/Info/1930303.

margin no longer than the maintenance level. She will receive a margin call if the price of margined stock drops and/or the price of shorted stock increases such that the account margin drops below the maintenance level. The position will be forced to close if she fails to meet the margin call within two trading days. In calculating the account margin, the collateral value is the discounted value of stocks purchased on margin or sold short. The discount rate varies with asset type and individual stocks.

4. Market reaction to removal of the bans on short-selling and margin-trading

4.1. Data

We collect information concerning the designated stock list and revisions from exchange websites[3]. The following data are retrieved from China Stock Market Trading Research Database (CSMAR) provided by GuoTaiAn Company, including (1) daily stock returns, (2) daily short-selling volume, margin-trading volume, and covering volumes for eligible stocks, (3) financial statement information, and (4) high frequency quote and trade data.

The sample period spans from January 1, 2010 to May 31, 2012. We have 292 addition events and 7 deletion events in total. Due to the very small sample, we drop the 7 deletion events. Due to the lack of quote and trade data for ETFs and their special features, we drop the 7 addition events for ETFs. Thus, we focus on the 285 additions events, among which 90 belongs to the first batch occurring on March 31, 2010 and 189 belongs to the second batch occurring on December 5, 2012. Among 285 additions events, three stocks were added to the list twice, with an interval over one and a half years from their respective first addition.

4.2. Event day returns

Following Chang et al. (2007), we calculate the abnormal returns around the addition events by two measures: market-model adjusted returns and market adjusted returns. To estimate the market model, we obtain daily returns during the period of one year and two

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

months before the events. This 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, denoted as day 0. Then we apply the pre-event estimation window of $[-290, -41]$ trading days, with a minimum of 180 trading days[4]. We estimate the OLS market model by regressing the time series of stock i's daily returns (R_{it}) on the market returns R_{Mt}: $R_{it} = \alpha_i + \beta_i R_{Mt} + \epsilon_{it}$, where the market portfolio is the value-weighted return of all stocks traded in the A-share market, using the market capitalization of public float as the weight. After obtaining the estimated α and β for each stock-event, we calculate the market-model adjusted abnormal return $AR_i^m(t)$ for stock i at event day t as $AR_i^m(t) = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{Mt}$. Then, we calculate $CAR_i^m[t_1, t_2]$, the cumulated abnormal return during the event window $[t_1, t_2]$, inclusively, using the market-model-adjusted abnormal return $AR_i^m(t)$.

To avoid potential estimation errors from the market model, we apply an alternative measure: the market-adjusted abnormal return $AR_i^a(t)$, defined as $AR_i^a(t) = R_{it} - R_{Mt}$. Then, we calculate $CAR_i^a[t_1, t_2]$, the cumulated abnormal return during the event window $[t_1, t_2]$, inclusively, using $AR_i^a(t)$.

We have 267 firm-events with available data on the effective dates. Table 2 reports the cross-sectional average of raw returns, abnormal returns, and cumulated abnormal returns around the addition events. Panel A shows the cross-sectional average of daily (abnormal) returns around the event days. First, we observe an average raw return of -1.87% on day zero. After adjusting for the predicted return by the market model, the abnormal return is on average -44.5 bps, significantly negative. The abnormal return adjusted by the market return is on average -66.0 bps, significantly negative. Second, although we observe positive returns on day one, the magnitude is much smaller than that on day zero. Panel B reports the cumulated returns during various event windows. $CAR^m[-5, -1]$, the cumulative abnormal

[4] The pre-event window in Chang et al. (2007) is [-280,-31]. In our sample, the time interval between the announcement date and effective date when the scheme was initially implemented was as long as one month and a half (34 trading days). To avoid the potential contamination by the announcement event, we advance the estimation window used in Chang et al. (2007) by ten trading days and use $[-290, -41]$ instead.

return adjusted by the market-model, is on average -73.9 bps, significantly negative. Since the addition event has been expected, certain trading activities in advance may result in this price drop before the event. $CAR^m[0,2]$ is on average -31.4 bps, significantly negative, and $CAR^m[0,5]$ in an average -73.3 bps, also significantly negative. Cumulated abnormal returns remain significantly negative for event windows of $[0,10]$, $[0,30]$, and $[0,60]$. For the robustness check, the magnitude and significance for the cumulated market-adjusted abnormal return (CAR^a) are qualitatively similar.

Figure 1 plots the cross-sectional mean of abnormal returns from the market-model ($AR^m[t]$) and the cumulated abnormal return beginning from event day -5 ($CAR^m[-5,t]$), during the event window of $[-5,+25]$ relative to the event day. We observe a clear downward trend in CAR^m throughout these thirty trading days around the addition event. The pattern seems persistent and not followed by evident reversal.

Overall, the market reaction to the addition event is consistent with the negative abnormal returns found in Chang et al. (2007) and Sharif et al. (2012b). The results confirm our conjecture that, even though both short-selling and margin-trading are banned before the event, the constraint on short-selling is more binding. Hence, upon the removal of bans, the overvaluation caused by short-selling constraint results in price drop.

4.3. Change in return distributions

Following Chang et al. (2007) and Bris et al. (2007), we compare the stock return distributions before and after the event. The pre-event window is $[-125,-1]$ trading days relative to the addition event, and the post-event window is $[1,125]$. We use the $[-375,-126]$ pre-event estimation window to re-estimate the OLS market model and then re-calculate the market-model adjusted abnormal returns during the pre-event window. In total, we have 262 firm events with paired abnormal returns available. Following Diether et al. (2009a), we calculate alternative volatility measures. The price range is defined as the daily high minus low scaled by high. *Variance* is defined as the average squared raw returns for a stock. $SemiVar^-$ ($SemiVar^+$) is defined as the average squared negative (positive) returns.

The comparison results are reported in Table 3. We observe significantly higher returns, marginally higher volatility, less positively skewed returns, and marginally less kurtosis after removal of the bans. In addition, we observe a higher frequency of extremely negative return in the post-event period. Higher volatility is expected to be associated with higher required rate of return, and we accordingly observe higher average returns after removal of bans. Reduced skewness is consistent with the findings in Chang et al. (2007) and Bris et al. (2007). Besides, the finding of more occurrence of extreme returns after the event is consistent with Chang et al. (2007). These two pieces of evidence support Xu's (2007) model but contradict Hong and Stein (2003). Both price range and *Variance* are significantly higher after the events. A closer examination reveals that $SemiVar^-$ does not increase significantly, where as $SemiVar^+$ experiences significant increase. Therefore, we find increased volatility in the up-market, not in the down-market. Arguably, short-selling constraint is more likely to be binding in the down-market whereas margin-trading constraint works in the up-market. The semivariance comparison reveals that margin-trading constraint effectively reduces volatility. The impact of short-selling constraint, however, is not to reduce the volatility, but to change the skewness.

4.4. Change in efficiency

Next, we examine whether short-selling constraint or margin-trading constraint harms market efficiency (Bris et al., 2007). First, we examine the sensitivity of stock return to market returns (β), as well as the R^2 measure. Morck et al. (2000) propose that higher synchronicity, measured by higher R^2, indicate lower efficiency since less firm-specific information is reflected in stock prices. We utilize daily returns during the pre-event window of $[-125, -1]$ trading days and the post-event window of $[1, 125]$ to estimate the OLS market model. In addition, we estimate the market model separately conditioning on negative (positive) market returns, and denote the beta coefficient as β_- (β_+) and the adjusted R^2 as R^2_- (R^2_-). Second, we estimate the cross-autocorrelation ρ between stock return and the lagged market return, conditioning on the direction of the lagged market, also. Higher ρ indicates greater price delay, and therefore lower efficiency. In estimating the market model or cross-autocorrelation, we require a minimum 90 trading days for the full sample, and a minimum 45 trading days for subsamples.

The average β, R^2, and ρ are reported in Table 4. We find that β increases significantly after removal of the bans, in both down- and up-market. This suggests that stock prices incorporate market-wide news faster after short-selling and margin-trading are allowed. β_-, the downside beta, increases more than β_+ does. Before the event, β_+ is significantly higher than β_-, whereas this asymmetry disappears after bans are removed. This confirms the previous conjecture that short-selling constraint had been more binding than margin-trading constraint, especially in hindering the pricing of market-wide information. Higher beta also echos the higher average return after removal of bans. In addition, we surprisingly find that the unconditional R^2 and the down-market R^2_- does not change significantly. The up-market R^2_+, however, increase significantly, suggesting less firm-specific information and therefore lower efficiency in the up-market. R^2_- is significantly higher than R^2_+ before the event, whereas R^2_- is significantly lower than R^2_+ after the event. Consistently, the unconditional cross-autocorrelation ρ and the down-market ρ_- does not change significantly. ρ_+ increases significantly, suggesting greater price delay and therefore lower efficiency in the up-market only, after short-selling and margin-trading are allowed.

At this stage, we are not able to determine whether the lower efficiency in the up-market is contributed by short-sellers or margin-traders, since we do not know their trading strategy yet. We will go back to this question in Section 5 and 6.

4.5. Change in liquidity

We next investigate the change in market quality, measured by depth, spreads, and order imbalance. We first follow Corwin and Schultz (2012) and estimate the bid-ask spread using daily high/low prices without transaction data. We use a pre-event window of $[-125, -1]$ trading days and the post-event window of $[1, 125]$. Next, we follow Diether et al. (2009a) and construct the quoted spread, effective spread, and realized spread using high-frequency trade and quote data. Here we use a pre-event window of $[-91, -1]$ calendar days and post-event window of $[1, 91]$. The quoted spread is the difference between contemporaneous bid-ask quote. The effective spread is the difference between contemporaneous price and mid-quote. The realized spread is the difference between price and the mid-quote after 5 minutes. Spread at transaction level is averaged to obtain the daily spread for each stock. We report the spread in dollar value as well as in percentage, which is dollar spread scaled by mid-quote. To measure depth and order imbalance, we use the quantity associated with the best quotes as the bid-depth and ask depth. The relative depth is the bid- minus ask-depth scaled by the average depth. Depth at transaction level is averaged to obtain the daily depth for each stock. Buy imbalance is the difference between buyer-initiated and sell-initiated trading volume during the day. The buy-sell indicator is identified by the exchange and explicitly reported in CSMAR dataset. Finally, we follow Easley et al. (1996) to calculate PIN. Since the number of trades per record is not reported for stocks traded on shanghai exchange, we treat one updated quote as one trade, if the associated trade volume is nonzero. We report estimated PIN separately for stocks traded on Shanghai exchange and Shenzhen exchange. Readers are reminder that PIN estimation for stocks listed in Shanghai exchange is not reliable.

The comparison results are reported in Table 5. We observe weak evidence that quoted spread and effective spread in dollar value drop marginally, but Wilcoxon test reveals that the drop is insignificant. Four percentage spreads increase significantly, supported by both paired t-test and Wilcoxon test. It seems that liquidity deteriorates after short-selling and margin-trading are allowed. This finding is consistent with Sharif et al. (2012a), who conjecture that short-seller and margin-traders are informative traders, which makes uninformed retail investors intimidated and quit the market, leading to deteriorated liquidity after the event. PIN measures price informativeness. However, we observe no higher PIN for stocks traded on Shenzhen exchange after the event, which contradicts the conjecture by Sharif et al. (2012a). An alternative explanation is deteriorated liquidity in the bear market, supported by significantly lower asset price after the event (Table 3). Since we do not control for the impact of the market trend, we hesitate to relate the changed market quality to short-selling or margin-trading activities.[5] We will perform additional cross-sectional test in Section 6. Finally, we observe no significant change in the relative depth. We observe more sell orders before the event, but more balanced order after the event.

5. Short sales and margin trading activities

In this section, we utilize the panel data of daily short-selling and margin-trading activity to infer the trading motivation, trading strategy as well as profitability of Chinese investors.

5.1. Summary statistics

We report the summary statistics for short-selling, margin-trading, and covering activities in Table 6. Statistics for short-selling and related covering activities are reported in Panel A, and statistics for margin-trading and related covering activities are reported in Panel B. Both panels reveal that short-selling and margin-trading are becoming more popular. Not all shortable stocks were shorted in 2010, and the volume was quite low. In comparison, margin-trading seems more popular than short-selling. All marginable stocks were ever purchased on margin even in 2010, and the margin volume is much higher than short volume in every year. E.g., in the first five months of 2012, less than 1% of trading volume was contributed by short-sellers, and more than 5% of volume was executed by margin-traders.

Several facts may contribute to such trend. First, the loan fee of short-selling may be more expensive than the interest charge for margin-trading (see Section 3). Second, the up-tick rule adds to the difficulties of short-sales. Third, short-selling itself is more risky than margin-trading. Theoretically, through buying stocks on leverage, the upside profit potential is unlimited and the downside loss potential is limited. In contrast, by short-selling, the

[5] As we have introduced in Section 3, stocks eligible for short-selling or margin trading are index constituents, which are special in firm size, growth, liquidity, etc. Thus, it is difficult to find a good match and examine the difference in difference as Sharif et al. (2012a) did.

upside profit potential is limited and the downside loss potential is unlimited. Since Chinese investors are new to the short-selling mechanism, many investors choose to steer away from it.

5.2. How do short sellers react to past returns?

As we summarize in Section 2.2, Diether et al. (2009b) propose four possible motivations of short sales. First, short sellers have superior negative information. Second, they have superior skills in identifying overvalued stocks. Third, they step in to provide liquidity at a profit in case of temporary buy-order imbalance. Lastly, they speculate when the volatility is high, which does not guarantee profitability. In this section, we adopt the panel regression methodology to infer the trading motivations of Chinese short-sellers.

Diether et al. (2009b) document that U.S. short-sellers are able to identify overpriced stocks, and they short sell more as the past return rises, especially when they become cross-sectional "winners". Accordingly, we regress $Short_t$, the stock short-selling turnover on day t, on r_{t-1}, the past stock return on day $t-1$.[6] Detailed variable definitions and summary statistics are reported in Table 7. We use the Augmented Dickey-Fuller unit-root test and reject the null hypothesis of no unit root in the time-series of daily short turnover. We accordingly take its first difference to stabilize the time series and thus the dependent variable is daily change in short turnover ($Short_t - Short_{t-1}$) at stock level. To deal with the serial correlation and cross-correlation, we estimate standard errors that cluster by both stock and calendar date (Thompson, 2011).[7]

The regression results are shown in Table 8. In sharp contrast to the positive coefficient

[6] We also use the past return during the five-day window of $[t-5, t-1]$ as in Diether et al. (2009b). We still observe a significantly negative relation between past return and today's short turnover. However, past returns during the five-day window has much lower explanatory power than the past one-day return in terms of R^2. Since the Chinese market is flooded with speculative trades (Mei et al., 2009), arguably Chinese investors are more likely to be myopic and respond to the most recent trading day. Hereby, we examine investor's trading behaviors in response to the past one day return only.

[7] The standard errors take into account of the clustering by both stock and calendar date. Consequently, stock characteristic such as dual-listing status as A- and H-shares in Hong Kong, or A- and B-shares, listing exchange do not show effects in the regression.

reported in Diether et al. (2009b), we find a significantly negative relation between r_{t-1} and short turnover in column (1). Then we identify the past winner and loser and find that Chinese short-sellers short sell more for past losers and less for past winners, again contradicting Diether et al.'s (2009b) result. It appears that the trading strategy of Chinese short-sellers is not to identify overvalued stocks, but to chase the trend, and short-selling mechanism simply provides them with a leveraged way to execute the "momentum" strategy in the down-market. Then we include more control variables to examine the remaining trading motivations. First, r_t, the contemporaneous return has a positive coefficient, consistent with Diether et al. (2009b). Second, $oimb_t^+$, the contemporaneous buy-order imbalance, has a negative coefficient, consistent with the liquidity providing hypothesis that investors short sell more in stronger buy-order imbalance. Third, σ_t has a positive coefficient, consistent with the speculating hypothesis, as short-selling volume is higher as the contemporaneous volatility is higher. In addition, the coefficient on $spread_t$ is positive, suggesting more short sales as the spread is low. Therefore, the high volatility is induced by divergent opinions instead of information asymmetry, since order competitiveness drives spread low.

Since Chinese short-sellers behave in a substantially different way from U.S. short-sellers, we are interested to know whether they possess superior information or skills at all. Technical analysis is one of the most popular "skills" adopted to identify "trend" and design trading strategy in China (Chen and Li, 2006). We follow Brock et al. (1992) to identify four technical indicators. The first two follow the moving average (MA) rule, and the last two follow the trading range breakout (TRB) rule. We assign a dummy $Down^{MA}$ that equals one if the stock price drops and crosses over the past 20-trading day's moving average, which indicates an established downward trend and is thus a sell signal. Similarly, Up^{MA} equals one if the price rises and crosses over the 20-day moving average, which is a buy signal. We assign a dummy $Down^{TRB}$ (Up^{TRB}) that equals one if the stock price drops (rises) and penetrates the past 250-trading days' minimum (maximum). The implication of TRB indicators is ambiguous. Brock et al. (1992) and George and Hwang (2004) propose $Down^{TRB}$ to be a strong sell signal and Up^{TRB} to be a strong buy signal. However, the contrarians may propose that trading range breakout is more likely followed by a reversal and thus $Down^{TRB}$ is a buy signal and Up^{TRB} is a sell signal. "Loser" ("Winner") equal one if the stock return ranks among the bottom (top) quintile and zero otherwise. We adopt these two MA indicators, two TRB indicators, as well as "Loser" and "Winner" to predict short-sellers trading behaviors.

The results are reported in columns (4) to (9) of Table 8. We observe a consistently negative coefficient on the historical return, confirming Chinese short-sellers as trend-chasers. In addition, the positive coefficient on $Down^{MA}$, the negative coefficient on Up^{MA}, the negative coefficient on $Down^{TRB}$, and the negative coefficient on $Winner$ suggest that Chinese investors indeed reply heavily on the technical trading rules. They seem to follow the buy and sell signals generated by MA rules and interpret TRB indicators as reversal signals. The cross-sectional winner is expected to continue as the winner in one-day window. These six dummies, combined with return on day $t-1$, predict 1.11% of variance in day t's short turnover (column 8).

To sum up, we find strong evidence that Chinese short-sellers do not identify mispricing. Instead, they seem to follow the technical trading rules to identify trend and chase the trend. We will examine whether they correctly identify the trend, either through superior information or superior skills, by investigating the return predictability in Section 6. They speculate on stocks with divergent opinions. They seem to provide liquidity by short-selling in buy-order imbalance.

5.3. How do margin traders react to past returns?

Following the methodology in the previous section, we propose four motivations of margin trading as well. First, they possess private positive information. Second, they have better skill to identify underpriced stocks. Third, they buy stock on margin in temporary sell-order imbalance. Fourth, they voluntarily bear more risk and speculate. We examine these trading motivations using panel regressions.

Regression results are reported in Table 9. First, we find that past return is positively associated with today's margin-trading turnover, and past winners are purchased more on margin. This is strong evidence that margin-traders are trader-chasers, not arbitrageurs who identify underpriced stocks. Besides, margin-traders seem to faithfully follow the instructions by short-term technical indicators: as yesterday's price drops below the 20-day moving average, today they buy less on margin. Instead, if yesterday's price goes above the 20-day moving average, they buy more on margin today. Since Chinese short-sellers and margin-traders are the same group of people, it is not surprising that they adopt consistent trading philosophy. Margin-traders seem to ignore the TRB signals. These six dummies, together with past return, predict .23% of variance in margin turnover (column 8), lower than the R^2 when we use those technical indicators to predict short turnover. $oimb^-$ has a insignificantly positive coefficient. Thus we fail to find liquidity provision in sell-order imbalance by margin-traders. σ has a significantly negative coefficient, indicating intensified margin-trading activity when the volatility is low. This is consistent with the destabilization function played by margin-traders proposed by Hardouvelis and Peristiani (1992). The coefficient on spread or turnover are insignificant.

To sum up, Chinese margin-traders do not identify undervaluation either. They try to identify trend and chase the trend. They still rely on technical analysis, but to a less extent than short-sellers. We will also examine whether they correctly identify the trend by investigating the return predictability in Section 6. Margin-traders do not provide liquidity in sell-order imbalance. They margin trade more as the volatility is low.

5.4. Covering of short or margin positions

Using currently available data, we are not able to associate the covering behavior with their original short-selling or margin positions. However, from the cross-sectional variations in covering turnover changes, we can infer their trading strategy to a certain extent.

We regress the daily covering turnover on past returns and technical indicators using panel data. The results are reported from columns (1) to (5) under the label $Cover_t^{SS}$ in Table 10. To make the maximum profit, short-sellers should cover the short position at the local price minimum and just before the price goes up. Thus, we expect more covering of short position to follow negative returns. It is also possible that if the price rises substantially after the short position is established, the investor may be forced to close the short position, leading to a positive association between past return and short covering. In column (5), we observe a significantly negative coefficient on r_{t-1}, consistent with the voluntary covering of short positions. This indicates that short-sellers are, to a certain extent, able to capture the short-term trend in closing the short position and realize the profit, if there is any. They still reply on technical analysis and use the same philosophy to interpret technical indicators: penetrating 250-day low is interpreted as a reversal signal, and thus associated with more covering of short positions. Cross-sectional winner or loser is expected to continue as winner or loser, and thus associated with more short covering and less short covering, respectively.

We have observed more short-selling in more buy-order imbalance in Table 8. To be profitable in providing liquidity, short-sellers should close the short position as the buy-order imbalance reverses. Inconsistent with the liquidity providing hypothesis, however, neither $oimb^{-}$ nor $oimb^{+}$ is significantly associated with covering of short positions. Therefore, the "liquidity provision" behavior shown in Table 8 cannot be intentional. Besides, we observe increased short covering in high volatility and high lagged turnover ratio, suggesting short covering as speculating activity also.

In columns (6) to (10) labeled with $Cover^{MG}$, we report the results of regressing covering turnover of margin positions on past returns and other explanatory variables. The model explanatory power is quite low. We find some clues that, similar to short-sellers, margin-traders interpret and cross-sectional loser as a sell signal. Inconsistent with the previous philosophy, crossing-over short-term moving average from above is associated with less covering of margin position, although only marginally. The coefficient of σ is negative, suggesting both intensified margin-trading and covering of margin positions in lower intra-day volatility, confirming margin-traders as market destablizers.

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

In Section 5, we rejected liquidity-provision as a potential trading motivation. In this section, we examine whether short-seller or margin-traders are able to predict future returns. If short-sellers or margin-traders possess superior information or skills to identify the trend, then their trades should predict future returns. In other words, intensified short-selling activity should be associated with lower future return, and intensified margin-trading activity should be associated with better future return. Besides, intensified covering of short position indicates a higher likelihood that the downward trend is over and an upward trend is to begin and therefore higher future return. Intensified covering of margin positions, however, indicates lower future return. Although we cannot match covering activities to the original short or margin positions and hence cannot calculate the profitability, we can still form the best conjecture whether trades are profitable within a certain investment horizon.

6.1. Portfolio returns

As we mentioned in Section 3, the maximum maturity of short or margin positions is six months, and short-selling and margin-trading are both costly. In addition, the turnover rate in Chinese stock market has been extraordinarily high. E.g., in Table 7, the daily turnover rate of sample stocks is average 1.12%, which suggests that on average, the ownership of a stock changes hand for 2.8 times per year. Hence, we do not expect the short or margin position to remain open for a long period. Since Chinese investors rely on the past one day return to make investment decision (Section 5), we adopt a one-day forecast horizon.

On each day t, we form five portfolios by short turnover $Short_t$ using all available shortable stocks in our sample. Then we compute the equal-weighted abnormal returns on day $t+1$. To avoid the impact of bid-ask bounce, the abnormal return is obtained by the bid-to-bid return on day $t+1$ minus the predicted return from the market model. We estimate the OLS market model by a rolling window of $[-280, -31]$ trading days, with a minimum of 180 trading days. The portfolios are rebalanced daily.

We report the portfolio returns in panel A of Table 11. Surprisingly, we find that the portfolio with lowest short turnover has a slightly negative return on the following day. The portfolio with highest short turnover, however, has a positive return of 29.03 bps on the next day. The strategy to long the heavily-shorted quintile and short the slightly-shorted quintile yields an abnormal return of 31.68 bps on the next trading day, statistically significant. The annualized return is as high as 76.7%, which is hard to reconcile with the superior information or skill hypothesis. Second, we form portfolios by margin turnover $Margin_t$. We hold it for a day and calculate the average bid-to-bid abnormal return on day $t+1$. Panel B shows that the slightly-margined quintile has 8.21 bps abnormal return whereas the heavily-margined quintile has almost zero returns. The strategy to long the slightly-margined quintile and short the heavily-margined quintile yields a significant daily return of 8.16 bps, which translates to an annualized return of 20.4%. This again contracts the superior information or skill hypothesis.

Third, we first form five portfolios by $Short_t$. Then within each $Short_t$ quintile, we form five portfolios by $Margin_t$. We hold these 25 portfolios for one day and obtain the abnormal returns on day $t+1$, reported in Panel C. We find that the strategy to long heavily-shorted quintile and short slightly-shorted quintile yields significantly positive returns in three out of five $Margin$ portfolios. The strategy to long slightly-margined quintile and short heavily-margined quintile yields significantly positive returns in two out of five $Short$ portfolios.

In short, the evidence strongly contradicts the hypothesis that short-sellers or margin-traders possess superior information or skill in identifying trend. At least they are not able to identify the best timing to trade, as their profit deteriorates substantially on the following day. The results reported in Table 11 are qualitatively unchanged when we adopt the value-weighted mechanism to obtain portfolio returns or when we examine a forecast window of $[t+1, t+5]$. The results are not reported for brevity.

6.2. *Cross-sectional regression*

Then we use the cross-sectional regression to examine the return predictability at stock level using panel data. We use the future return as the dependent variable, and today's short turnover, margin turnover, covering of short turnover and covering of margin turnover as the explanatory variable. We follow Diether et al. (2009b) to use the standard errors clustered by both the calendar date and by stock.

The regression results are reported in columns (1)-(3) of Table 12. Cross-sectionally, intensified short activity today is associated with better return on the next day. Intensified margin activity today, however, is associated with deteriorating return on the next day. This result is consistent with the findings in the portfolio analysis, suggesting that Chinese short-sellers or margin-traders fail to correctly predict future returns, at least on one-day ahead basis. Furthermore, we examine whether past technical indicators correctly predict future returns. Ex post, $Down_{t-1}^{MA}$ is positively associated with day $t+1$ return, and $Down_{t-1}^{TRB}$ is negatively associated with day $t+1$ return. Therefore, crossing-over the short-term moving average from above seems to followed by reversal. Breaking-out the trading range of long-term minimum, however, seems to be followed by a sustained downward trend. Up_{t-1}^{TRB} has a marginally negative coefficient. Besides, $Winner_{t-1}$ is negatively associated with day $t+1$ return, consistent with Diether et al. (2009b) who consider the cross-sectional top quintile stocks as overvalued stocks. Recall from Section 5 that, $Down_{t-1}^{MA}$ is used as a sell signal, and Up_{t-1}^{MA}, $Down_{t-1}^{TRB}$, and $Winner_{t-1}$ are used as buy signals (see Tables 8 and 9). Hence, short-sellers and margin-traders seem to mistakenly interpret the implications of $Down^{MA}$, $Down^{TRB}$ and $Winner$.

We perform robustness checks by examining the future returns during $[t+1, t+5]$ trading days. Results are reported in columns (4)-(6) in Table 12. The predictive power of short activity seems weaker. Its coefficient is still positive, but significant only in column (4). The predictive power of margin activity remains strong, indicating that intensified margin-trading activity predicts lower future return in the next week. The signs and magnitudes of coefficients on technical indicators are similar to the results for AR^bb_{t+1}.

As the robustness checks, we check the predictability of trading activities for subsamples such as small/large firms, growth/value firms, firms with high/low institutional ownership, firms with high/low spread, firms with high/low prices, firms with high/low stock turnover, etc. The baseline results reported in Table 8 remain qualitatively unchanged. The predictive power of day t trading activity for day $t+1$ return is stronger for large or value firms, or firms with low institutional ownership, high price level, low spread, or low stock turnover. The subsample regression results are not tabulated for brevity.

Overall, the results in these two sections contradict Diether et al. (2009b), Boehmer et al. (2008), Cohen et al. (2007), and Takahashi (2010), which find short-sellers or margin-traders to be possess superior information and able to predict the future returns. In our study, however, short-sellers or margin-traders seem to possess no superior information or better skills to identify the good timing of trade or design the right trading strategy. Their trading behaviors do not predict the future. Furthermore, trading in their opposite direction produces economically and statistically returns.

6.3. Order imbalance

In section 5 we show that Chinese investors short sell more in stronger buy-order imbalance and narrower bid-ask spread (Table 8), but the covering of short positions are not related to order imbalance at all 10. In this section, we examine the relation between trading activity and future order imbalance to future refute liquidity provision as a potential trading motivation. Investors short sell in strong order-imbalance only when they predict this order imbalance to be temporal. If not, the high security-lending fee will chew up the thin profit from liquidity provision. We use $t+1$ sell- and buy-order imbalance as the independent variables in the panel regression. Table 13 reveals that intensified short activity is followed by no changes in buy-order imbalance and weaker sell-order imbalance. It suggests that since the buy-order imbalance does not reverse in one day horizon, the liquidity provision by short-sellers is not immediately profitable.

Even though we find no evidence that margin-traders provide liquidity in sell-order imbalance in table 9, we observe that intensified margin-trading activity is followed by severer buy-order imbalance and sell-order imbalance as well in Table 13. If investors margin trade in order to provide liquidity in sell-order imbalance, this imbalance is not temporal either, persisting for at least another day.

Next we examine the impact of short-selling and margin-trading on liquidity. Table 5 has revealed widening spread after short-selling and margin-trading are allowed. Besides, Table 8 has shown intensified short-selling activity coinciding with higher volatility and narrower spread, consistent with the speculation behaviors in divergent opinions. After the opinion converges, the volatility drops and spread widens. In column (5) and (6) of Table 13, we report the regression results using $t + 1$ spread as the dependent variable. Consistent with the speculation hypothesis, intensified short-selling activity is followed by widening spread. We also find evidence that intensified covering of short positions is followed by widening spread, but fail to find a discernible relation between margin activities and future spread.

6.4. Volatility

In section 5, we have shown increased short-selling and associated covering coinciding with higher volatility (Tables 8 and 10) and increased margin-trading and associated covering coinciding with lower volatility (Tables 9 and 10). In this section, we examine whether those activities contribute to additional future volatility. $SemiVar^{-}_{t+1}$ ($SemiVar^{+}_{t+1}$), measured using transaction data on day $t + 1$, is the dependent variable in regressions. We obtain the return between transactions and calculate the sum of squared negative (positive) transaction returns as $SemiVar^{-}_{t+1}$ ($SemiVar^{+}_{t+1}$). Besides, we calculate the skewness of transaction returns on day $t + 1$.

The regression results are reported in Table 14. Contrary to the traditional wisdom, short-selling does not contribute to higher volatility, in either up- or down-market, at least in one-day ahead horizon. Since short-sellers do not possess superior information or skills, we conjecture that by speculating in a randomly way, short-sellers does not add into additional divergence of opinions or information asymmetry and thus no changes in volatility or skewness. The covering of short positions is followed by returns with lower volatility and less positive skewness, which indicates higher probability of negative returns. The margin-trading and associated covering, however, are associated higher future volatility and marginally more positive skewness. This confirms our observation in section 5 that margin traders intentionally trade in low volatility, create excess volatility and destabilize the market.

6.5. Efficiency

We compute cross-autocorrelation ρ_{t+1} between stock return on day $t+1$ and lagged market return on day t in a overlapping window of $[t+1, t+5]$. In addition, we compute up(down)-state ρ^+_{t+1} (ρ^-_{t+1}) counting five trading days with positive (negative) lagged market returns, beginning from day $t+1$. Due to data limitation, we do not have stock return and the lagged market return at transaction level. As a compromise, we rely on the rolling five-day window to estimate the daily ρ measures. Readers are reminded to interpret the results in this section with cautions.

We regress cross-autocorrelation on past trading activities and report the results in Table 15. We observe that intensified short-selling is associated with higher future cross-autocorrelation, in both up- and down-market, especially in the up-market. It implies that short-selling reduces pricing efficiency in both up- and down-market. In addition, the covering of short position reduces efficiency in the down-state. It indicates that short-selling and associated covering actually reduces efficiency in China. Combined with evidence of intensified short-selling in case of strong buy-order imbalance (Table 8), we conjecture that short-sellers intentionally take positions opposite to potentially informative traders. Since their speculation is not driven by superior information or skills, their off-setting trades does not add to volatility but delay the pricing discovery. We observe no significant relation between margin trading and one-day ahead cross-autocorrelation. However, the intensified covering of margin position is associated with better pricing efficiency in the up-market.

7. Conclusion

In this study, we examine the impact of short-selling and margin-trading in the Chinese market from various perspectives. First of all, we examine the impact of bans on short-selling and margin-trading. We discover negative event returns when the bans are removed. Besides, after removal of the bans, we observe higher volatility, higher R^2, and higher cross-autocorrelation in the up-market. Then, we examine why Chinese short-sellers and margin-trader trade. We reject the superior information hypothesis since Chinese short-sellers or margin-traders fail to identify mis-pricing and fail to correctly predict future trend. They demonstrate no sophisticated skills beyond technical analysis and they mistakenly interpret implications of technical indicators. Although short-sellers short sell more in stronger buy-order imbalance, we reject the liquidity provision hypothesis, since we fail to find any relation between covering of short-position and order imbalance, and the order imbalance seems not transitory. Finally, we find supporting evidence that short-sellers speculate in high uncertainty and high divergence of opinions. We conjecture that, although short-sellers possess no information or skills, they intentionally gamble in the direction opposite to dominating investors, who are potentially "correct", resulting in no higher volatility but lower pricing efficiency. On the other hand, Chinese margin-traders seem not to possess superior information or skills either. They do not identify mis-pricing. They similarly use the technical analysis to identify and follow the trend, which also incorrectly predict future returns. We find no relation between margin-trading activity and order imbalance. However, we do find intensified margin-trading coinciding with low volatility and preceding high volatility, which supports margin-traders as market destabilizers. Overall, absent superior information or skills, the speculating behavior by Chinese short-sellers and margin-traders is not profitable.

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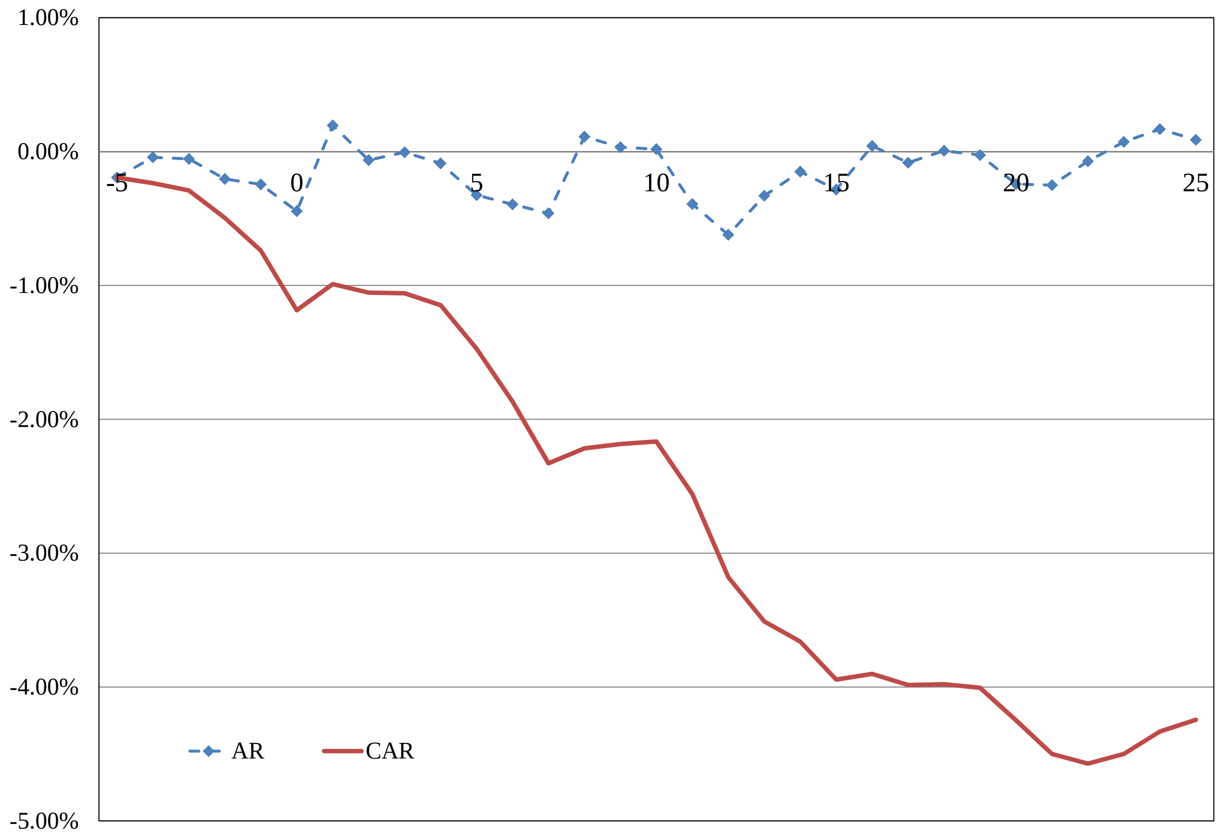

Figure 1: **Abnormal returns and cumulated abnormal returns around additions**
This figure reports the average abnormal returns and cumulated abnormal returns calculated based on the OLS market model around addition events, arranged by event days. Following Chang et al. (2007), an addition event is defined 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, denoted as day 0. For the market model, an estimation window of $[-290, -41]$ trading days, with a minimum length of 180 trading days, is applied. The horizontal line represents the event time in trading days relative to the addition event. The vertical line represents the abnormal returns or cumulative abnormal returns.

Table 1: **Summary statistics: List changes, addition events and deletions events**

This table reports the occurrence of events in which individual stocks listed on the Shanghai exchange and Shenzhen exchange experienced short selling and margin trading restrictions changes. "Effective date", in the format of yyyy/mm/dd, is the date on which a new version of the designated list of securities for short selling and margin trading took effect, and "announcement date", in the format of yyyy/mm/dd, is the date on which this new version of the list was announced. The remaining columns show the number of stocks added to or deleted from the designated list and the total number of stocks on the revised list, for Shanghai exchange, Shenzhen exchange, and both two exchanges, respectively. Among the seven deletions, six occurred in July 2010, three months after March 2010, when the six stocks were initially added to the list. The last deletion occurred in December 2011, one and a half years after March 2010 when the stock was initially added to the list. Among the six deletions in July 2010, three stocks were added back to the list in December 2011, with a time interval over one and a half years.

Effective	Announcement	Shanghai exchange			Shenzhen exchange			All		
date	date	Add	Delete	No. on list	Add	Delete	No. on list	Add	Delete	No. on list
2010/03/31	2010/02/12	50	-	50	40	-	40	90	-	90
2010/07/01	2010/06/21	4	4	50	1	1	40	5	5	90
2010/07/29	2010/07/16	1	1	50	-	-	40	1	1	90
2011/12/05	2011/11/25	134	-	184	62	1	101	196	1	285
2012/06/04	2012/06/01	1	-	185	1		102	2	-	287
Cumulated		190	5	185	104	2	102	294	7	287

Table 2: **Stock returns around additions**

This table reports the cross-sectional average of raw returns and abnormal returns based on the market model and the market adjusted model, around additions. Following Chang et al. (2007), 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, denoted as day 0. For the market model, an estimation window of $[-290, -41]$ trading days, with a minimum length of 180 trading days, is applied. Panel A reports the daily abnormal returns, and Panel B reports the cumulated daily abnormal returns, respectively.

Panel A: Daily abnormal returns around additions

		Raw return			Market model adjusted (AR^m)			Market adjusted (AR^a)		
Days	N	Mean	Median	t	Mean	Median	t	Mean	Median	t
-5	255	-0.016%	-0.109%	-0.20	-0.194%	-0.315%	-2.44	-0.154%	-0.273%	-1.96
-4	266	0.684%	0.927%	5.48	-0.042%	-0.143%	-0.53	0.159%	-0.006%	1.90
-3	267	-2.251%	-3.035%	-11.95	-0.055%	-0.200%	-0.60	-0.486%	-0.594%	-4.79
-2	267	2.217%	2.162%	19.54	-0.204%	-0.299%	-2.20	0.157%	-0.017%	1.73
-1	267	-1.132%	-1.046%	-10.91	-0.245%	-0.286%	-3.10	-0.403%	-0.477%	-4.80
0	267	-1.874%	-1.544%	-15.89	-0.445%	-0.503%	-4.41	-0.660%	-0.622%	-6.30
1	267	0.485%	0.564%	5.66	0.195%	0.206%	2.55	0.207%	0.266%	2.68
2	267	0.289%	0.139%	3.96	-0.064%	-0.185%	-0.90	0.004%	-0.160%	0.06
3	267	-0.091%	-0.149%	-1.05	-0.005%	-0.037%	-0.06	-0.002%	-0.032%	-0.03
4	267	-0.742%	-0.812%	-7.94	-0.088%	-0.076%	-0.99	-0.179%	-0.216%	-2.03
5	267	-1.496%	-1.429%	-12.95	-0.325%	-0.366%	-3.31	-0.485%	-0.387%	-4.82

Panel B: Daily cumulated abnormal returns around additions

		Raw return			Market model adjusted (CAR^m)			Market adjusted (CAR^a)		
Event windows	N	Mean	Median	t	Mean	Median	t	Mean	Median	t
$[-5, -1]$	264	-0.505%	-0.630%	-2.15	-0.739%	-0.914%	-3.77	-0.730%	-0.935%	-3.74
$[-1, +1]$	264	-2.549%	-2.458%	-11.23	-0.500%	-0.515%	-3.03	-0.867%	-0.848%	-5.01
$[0, +2]$	267	-1.100%	-0.913%	-6.14	-0.314%	-0.265%	-2.14	-0.449%	-0.399%	-3.01
$[0, +5]$	267	-3.428%	-3.206%	-14.01	-0.733%	-0.841%	-3.55	-1.116%	-1.103%	-5.49
$[0, +10]$	267	-6.290%	-6.117%	-12.90	-1.426%	-1.412%	-3.94	-2.133%	-2.270%	-5.68
$[0, +30]$	267	-12.015%	-13.078%	-16.24	-3.135%	-3.090%	-5.17	-3.512%	-3.290%	-5.45
$[0, +60]$	267	-6.396%	-1.729%	-5.91	-2.441%	-2.135%	-3.95	-1.075%	-1.303%	-1.71

Table 3: **Changes in return distribution and volatility**

This table reports the changes in stock characteristics, return distributions, and volatility around the addition events. Following Chang et al. (2007), 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, denoted as day 0. The columns labeled with "Pre" show the cross-sectional mean/median of the time-series average of variables during the pre-event estimation window of [-125,-1] trading days relative to the event day. The columns labeled with "Post" show the average of variables during the post-event window of [1,125]. A minimum of 90 trading days is required for both the pre-event and post-event window. We apply the paired t-test and the Wilcoxon nonparametric test to examine the statistic significance of the change in mean and median around the event, and report the t-value and associated p-value , as well as the p-value of Wilcoxon test in the last three columns. Following Diether et al. (2009a), we calculate the average closing prices and daily trading volume (in million shares) and report the statistics in Panel A. Following Chang et al. (2007) and Bris et al. (2007), we calculate the mean, standard deviation, skewness, kurtosis of abnormal returns, and the frequency of extreme return to occur (defined as the frequency of returns lower than two standard deviations below the mean) and report the statistics in Panel B. To calculate abnormal returns during the pre-event window of [-125, -1], we estimate the OLS market model using daily returns during the estimation window of [-375,-125] trading days and require a minimum of 180 trading days. To calculate the abnormal returns during the post-event window of [1,125], we estimate the OLS market model using daily returns during the estimation window of [-291,-41] trading days and require a minimum of 180 trading days. Following Diether et al. (2009a), price range is the difference between the highest and the lowest trading price divided by the highest price for a stock on a given day. Besides, *Variance* is the average squared raw returns with dividend based on closing prices for a stock. $SemiVar^{+}$ ($SemiVar^{-}$) is the average squared raw returns conditioning on positive (negative) returns for a stock. Following Chang et al. (2007), outliers with a value higher (lower) than three standard deviations above (below) the cross-sectional mean are trimmed and set to three standard deviations above (below) the mean.

		Pre		Post		Significance of differences		
		Mean	Median	Mean	Median	t-Ttest	p-Ttest	p-Wilcoxon
Mean	262	-0.072%	-0.047%	0.015%	0.006%	-5.36	0.000	0.000
SD	262	1.601%	1.632%	1.667%	1.646%	-1.71	0.087	0.198
Skewness	262	0.797	0.779	0.677	0.637	1.83	0.068	0.054
Kurtosis	262	3.555	2.459	3.032	2.206	1.78	0.075	0.175
Extreme values	262	1.450%	1.600%	1.632%	1.600%	-2.08	0.038	0.132
Price	273	18.365	13.295	15.284	10.887	14.39	0.000	0.001
Volume	273	27.119	12.539	22.086	14.460	1.36	0.175	0.151
Price Range	273	3.2101%	3.2410%	3.4017%	3.3884%	-7.29	0.000	0.001
Variance	273	0.0530%	0.0515%	0.0592%	0.0568%	-5.47	0.000	0.007
- $SemiVar^{-}$	273	0.0537%	0.0520%	0.0553%	0.0530%	-1.36	0.175	0.573
- $SemiVar^{+}$	273	0.0549%	0.0514%	0.0660%	0.0632%	-6.48	0.000	0.000

Table 4: **Changes in market efficiency**

This table reports the cross-sectional average of estimated measures of market efficiency. The columns labeled with "Pre" show the cross-sectional mean/median of during the pre-event estimation window of [-125,-1] trading days relative to the event day. The columns labeled with "Post" show the average of variables during the post-event window of [1,125]. A minimum of 90 trading days is required for both the pre-event and post-event window. We apply the paired t-test and the Wilcoxon nonparametric test to examine the statistic significance of the change in mean and median around the event, and report the t-value and associated p-value , as well as the p-value of Wilcoxon test in the last three columns. Following Chang et al. (2007), 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, denoted as day 0. Following Bris et al. (2007), for each stock, we estimate the OLS market model using the full sample of either the pre-event or the post-event estimation window. Besides, using only either positive (negative) market returns, we estimate β_+ (β_-) and R^2_+ (R^2_-). β_{Diff} is β_- minus β_+ and R^2_{Diff} is R^2_- minus R^2_+. We estimate the cross-autocorrelation coefficient ρ between stock return and the lagged market returns, and ρ_+ (ρ_-), the cross-autocorrelation coefficient conditioning on positive (negative) lagged market returns. We test whether β_{Diff}, R^2_{Diff}, and ρ_{Diff} are different from zero using the t-test and report the t-values in volumes labeled "Pre" or "Post".

		Pre			Post			Significance of differences		
		Mean	Median	t-value	Mean	Median	t-value	t-Ttest	p-Ttest	p-Wilcoxon
β	274	1.158	1.170		1.267	1.301		-7.97	0.000	0.000
β_-	274	1.092	1.123		1.291	1.305		-8.75	0.000	0.000
β_+	274	1.159	1.134		1.274	1.211		-4.45	0.000	0.004
β_{Diff}	274	-0.067	-0.086	-2.97	0.016	-0.005	0.64	-2.49	0.013	0.015
R^2	274	50.70%	51.29%		51.25%	50.96%		-0.73	0.468	0.647
R^2_-	274	32.01%	31.24%		31.09%	30.65%		0.37	0.709	0.700
R^2_+	274	30.36%	28.10%		35.12%	32.91%		-4.17	0.000	0.001
R^2_{Diff}	274	2.12%	1.50%	2.14	-3.37%	-3.11%	-3.25	3.83	0.000	0.001
ρ	276	0.709	0.720		0.715	0.724		-0.66	0.509	0.566
ρ_-	276	0.554	0.579		0.560	0.574		-0.46	0.649	0.778
ρ_+	276	0.544	0.552		0.590	0.605		-3.74	0.000	0.000
ρ_{Diff}	276	0.010	0.011	0.98	-0.030	-0.031	-3.20	2.89	0.004	0.003

Table 5: **Changes in market quality**

This table reports the change of market quality surrounding the addition events. An addition event is defined as one in which an individual stock is added to the list and therefore can be sold short or purchased on margin from the event day. Columns labeled "Pre" and "Post" report the cross-sectional average of the time-series average of daily variables during the 91 calendar days before and after the event. Column labeled "Diff" reports the differences and associated statistical significance between variables before and after the event. Following Corwin and Schultz (2012), we estimate "Spread (highlow)" based on daily high and low prices without transaction data. Following Diether et al. (2009a), we define the middle price mid as $(bid+ask)/2$, where bid and ask are the best quotations based on each quote updates. Quoted spread (in cents) is defined as $200 \times (ask - bid)$, and quoted spread (in bps) is defined as $10000 \times (ask - bid)/mid$, based on quote updates. For buyer-initiated trade, effective spread (in cents) is defined as $200 \times (price - mid)$, and effect spread (in bps) is defined as $[20000 \times (price - mid)/mid]$, where trades are matched to the contemporaneous quotation. For seller-initiated trade, effective spread (in cents) is defined as $200 \times (mid - price)$, and effect spread (in bps) is defined as $[20000 \times (mid - price)/mid]$. quotations are matched to the most updated price. For buyer-initiated trade, realized spread (in cents) is defined as $2(price - mid_{+5})$ and realized spread (in bps) is defined as $2(price - mid_{+5})/mid_{+5min}$, where each trade price is matched to the mid quote 5 minutes following the trade (whichever is nearer, but no more than 6 minutes). For seller-initiated trade, realized spread (in cents) is defined as $2(mid_{+5} - price)$ and realized spread (in bps) is defined as $2(mid_{+5} - price)/mid_{+5}$. Time-weighted statistics weigh each observation at quote level to daily measure by the number of seconds between this and the previous quote. Volume-weighted statistics weigh each observation by the trading volume of the trade. Following Diether et al. (2009a), quoted bid/ask depth (in 1000 shares) is the cumulative depth on each day, which is the time-weighted summation of the depth for the best bid/ask of each quote updates (a change in bid, ask, or quoted volume). Relative depth (in %) is defined as $100 \times (biddepth - askdepth)/(askdepth + biddepth)$. Buy imbalance (in 1000 shares) is the difference between buyers- and seller-initiated trading volume on each trading day. The buy-sell indicator is identified by the exchange. The percentage of buy imbalance is buy imbalance over summation of buyer- and seller-initiated trading volume on each trading day. PIN is estimated following Easley et al. (1996). Since the number of trades is not reported for stocks traded on shanghai exchange, we treat one updated quote as one trade if the trade volume is nonzero. Hence, we report estimated PIN separately for stocks traded on Shanghai exchange and Shenzhen exchange.

				Pre		Post		Significance of differences		
Variable	Weight	Unit	N	Mean	Median	Mean	Median	t-Ttest	p-Ttest	p-Wilcoxon
Spread (highlow)		%	273	0.777	0.776	1.106	1.076	-20.13	0.000	0.000
Quoted spread	Time	Cents	282	1.643	1.262	1.608	1.252	1.60	0.110	0.890
	Time	bps	282	12.774	11.572	14.639	13.368	-19.29	0.000	0.000
Effective spread	Volume	Cents	282	0.949	0.791	0.916	0.760	2.11	0.036	0.400
	Volume	bps	282	6.097	5.143	6.718	5.925	-10.71	0.000	0.000
Realized spread	Volume	Cents	282	0.698	0.371	0.974	0.398	-2.28	0.023	0.060
	Volume	bps	282	5.928	2.741	8.498	4.770	-2.63	0.009	0.019
Quoted bid depth	Time	million shares	282	4,690.013	430.950	4,181.034	536.593	1.00	0.320	0.074
Quoted ask depth	Time	million shares	282	2,665.601	425.296	2,935.138	487.616	-0.82	0.413	0.042
Relative bid depth		%	282	0.453	0.758	0.490	0.779	-0.10	0.923	0.913
buy imbalance		1000 shares	282	471.539	-0.120	408.809	0.011	0.75	0.453	0.000
		%	282	-2.009	-3.682	-0.375	-1.580	-7.16	0.000	0.000
PIN		%	258	11.253	10.394	12.409	11.582	-2.35	0.019	0.000
- Shanghai		%	171	10.072	9.126	11.920	10.803	-3.36	0.001	0.0000
- Shenzhen		%	87	13.574	12.998	13.371	13.131	0.21	0.834	0.950

Table 6: **Summary statistics for short selling and margin trading activities**
This table reports the summary statistics for short-selling, related covering of short positions, margin trading and related covering of margin position activities for years across exchanges. Panel A is shown for short-selling and related covering activities. Average daily short volume (covering volume of short positions), in the unit of 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 position) is the short (covering) volume scaled by daily total trading volume. Panel B is shown for margin trading and related covering activities. Average daily margin trading volume (turnover) and covering volume (turnover) of margin positions are defined in a similar way.

Panel A: short selling activity across exchanges and years			
	2010	2011	2012
No. of stocks eligible for short selling	96	278	278
- Shanghai	55	180	180
- Shenzhen	41	98	98
No. of stocks sold short	81	276	278
- Shanghai	44	179	180
- Shenzhen	37	97	98
Average daily short volume	5,298	82,485	133,933
- Shanghai	5,594	93,888	131,212
- Shenzhen	4,946	61,442	138,933
Average daily short turnover	0.016%	0.697%	0.719%
- Shanghai	0.010%	0.681%	0.621%
- Shenzhen	0.022%	0.727%	0.898%
Average daily covering volume of short positions	5,118	57,091	116,397
- Shanghai	5,307	57,340	115,398
- Shenzhen	4,893	56,633	118,230
Average daily covering turnover of short positions	0.016%	0.521%	0.690%
- Shanghai	0.010%	0.473%	0.607%
- Shenzhen	0.022%	0.609%	0.841%

Panel B: Margin purchase activity across exchanges and years	2010	2011	2012
No. of stocks eligible for margin purchase	96	278	278
- Shanghai	55	180	180
- Shenzhen	41	98	98
No of stocks purchased on margin	96	278	278
- Shanghai	55	180	180
- Shenzhen	41	98	98
Average daily margin purchase volume	301,469	506,292	902,684
- Shanghai	367,883	543,223	984,171
- Shenzhen	212,377	438,461	753,013
Average daily margin purchase turnover	0.777%	3.526%	5.044%
- Shanghai	0.702%	3.379%	4.959%
- Shenzhen	0.876%	3.796%	5.200%
Average daily covering volume of margin positions	244,751	401,395	801,545
- Shanghai	296,758	436,937	905,393
- Shenzhen	174,985	336,115	610,804
Average daily covering turnover of margin positions	0.615%	2.316%	4.281%
- Shanghai	0.547%	2.211%	4.393%
- Shenzhen	0.707%	2.507%	4.073%

Table 7: **Variable definition and summary statistics**

Panel A of this table shows the definition of variables. Panel B shows the cross-sectional summary statistics for time-series averaged variables. Following Brock et al. (1992), we identified four technical indicators: $Down^{MA}$, Up^{MA}, $Down^{TRB}$, and Up^{TRB}. *Loser*, *Winner*, *Spread*, *oimb*, $oimb^{-}$, $oimb^{+}$ and TV are defined following Diether et al. (2009b).

Panel A: Variable definition Name	Definition
Short	Short turnover = daily short volume/trading volume. Use its first difference in regressions.
$Cover^{SS}$	Covering turnover of short selling positions = Daily covering of short volume / daily trading volume. Use its first difference in regressions.
Margin	Margin turnover = daily margin volume / daily trading volume. Use its first difference in regressions.
$Cover^{MG}$	Covering turnover of margin positions = daily covering of margin volume / daily trading volume. Use its first difference in regressions.
$Down^{MA}$ (Up^{MA})	Equals one if the closing price goes down (up) and crosses over the past 20 trading day's moving average from above (below), and zero otherwise.
$Down^{TRB}$ (Up^{TRB})	Equals one if the closing price goes down (up) and breaks through the past 250-trading day's minimum (maximum), and zero otherwise.
Loser (*Loser*)	Equals one if return is among the bottom (top) quintile among all stocks, and zero otherwise.
r	Daily stock return with cash dividend.
Spread	Time-weighted average realized spread on each day. The realized spread is the difference between price for each trade matched to the mid-quote after 5 minutes. Use its first difference in regressions.
Oimb	Daily order imbalance = (daily buy volume - sell volume) /(total volume). Use its first difference in regressions.
$Oimb^{-}$ ($Oimb^{+}$)	Equals $\|Oimb\|$ if $Oimb < 0 (> 0)$ and zero otherwise. Use its first difference in regressions.
σ	Daily volatility = (day high-day low)/day high. Use its first difference in regressions.
TV	Daily share turnover = daily trading volume/share outstanding. Use its first difference in regressions.
Variance	Average squared transaction returns on a day. Use its first difference in regressions.
$SemiVar^{-}$ ($SemiVar^{+}$)	Average squared transaction returns on a day, conditioning on negative (positive) transaction returns. Use its first difference in regressions.
ρ	Cross-autocorrelation between stock return and the lagged market returns, estimated in a rolling window of [t+1, t+5] trading days. Use its first difference in regressions.
ρ^{-} (ρ^{+})	Cross-autocorrelation between stock return and the negative (positive) lagged market returns, estimated in a rolling window of 5 trading days ahead with negative (positive) lagged market returns. Stabilize ρ^{-} (ρ^{+}) by deducting the lagged ρ.

Panel B: Summary statistics

Variable	Unit	N. stocks	Mean	Max	Median	Min
Short	%	281	0.5181	2.0668	0.4482	0.0000
$Cover^{SS}$	%	281	0.4856	1.7919	0.4326	0.0000
Margin	%	281	4.2280	10.8730	4.0636	0.1172
it Cover^{MG}	%	281	3.5349	9.0644	3.4405	0.0355
$Down^{MA}$		281	0.0493	0.0897	0.0484	0.0203
Up^{MA}		281	0.0502	0.0966	0.0483	0.0203
$Down^{TRB}$		281	0.0551	0.5169	0.0508	0.0000
Up^{TRB}		281	0.0030	0.0490	0.0000	0.0000
Loser		281	0.2041	0.4015	0.2027	0.0878
Winner		281	0.2042	0.3904	0.2026	0.0850
r	%	281	0.0543	0.8879	0.0308	-0.4072
Spread	%	281	0.0374	0.1820	0.0340	-0.0684
Oimb	%	281	-0.0183	0.0732	-0.0180	-0.0975
$Oimb^{+}$	%	281	0.0482	0.1072	0.0478	0.0218
$Oimb^{-}$	%	281	0.0695	0.1492	0.0684	0.0260
σ		281	0.0324	0.0543	0.0327	0.0150
TV		281	0.0112	0.0638	0.0091	0.0002
Variance	%	281	3.3936	22.6379	2.4110	0.4679
$SemiVar^{-}$	%	281	3.3393	22.5246	2.3520	0.4528
$SemiVar^{+}$	%	281	3.4512	22.7511	2.4466	0.4837
ρ		281	0.6851	0.8990	0.7042	0.0372
ρ^{-}		281	0.6950	0.9145	0.7126	-0.0702
ρ^{+}		281	0.6754	0.8994	0.6977	0.0439

Table 8: **Panel regressions: Daily short selling turnover as dependent variable**

This table reports the regression results of daily short-selling turnover $Short_t$ on yesterday's return r_{t-1} using panel data. Variables are defined in Table 7. The standard errors take into account clustering by calendar date and by stock (Thompson, 2011). T-statistics are reported within parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.0031	0.0201*	0.0019	0.0022	0.0123	0.0068	0.0176	0.0209*	0.0160
	(0.27)	(1.67)	(0.17)	(0.19)	(1.03)	(0.58)	(1.43)	(1.73)	(1.30)
r_{t-1}	-0.0331***		-0.0321***	-0.0304***	-0.0205***	-0.0348***	-0.0251***	-0.0235***	-0.0224***
	(10.71)		(8.92)	(10.03)	(4.02)	(10.76)	(4.71)	(5.00)	(4.21)
$Down_{t-1}^{MA}$				0.0622***	0.0697***			0.0602***	0.0628***
				(3.94)	(4.48)			(3.87)	(4.12)
Up_{t-1}^{MA}				-0.0457***	-0.0363**			-0.0394**	-0.0353**
				(2.87)	(2.54)			(2.53)	(2.46)
$Down_{t-1}^{TRB}$						-0.0717***	-0.0702***	-0.0617***	-0.0634***
						(4.46)	(4.03)	(3.84)	(3.71)
Up_{t-1}^{TRB}						0.0266	0.0193	0.0287	0.0126
						(0.74)	(0.60)	(0.82)	(0.39)
$Loser_{t-1}$		0.0547***			0.0205		0.0204	0.0061	0.0197
		(6.63)			(1.60)		(1.59)	(0.49)	(1.54)
$Winner_{t-1}$		-0.1480***			-0.0840***		-0.0832***	-0.0875***	-0.0836***
		(13.17)			(5.31)		(5.23)	(5.48)	(5.27)
r_t			0.0081**		0.0083**		0.0082**		0.0083**
			(2.14)		(2.26)		(2.24)		(2.26)
$oimb_t^+$			0.2785***		0.2809***		0.2827***		0.2808***
			(5.22)		(5.39)		(5.40)		(5.37)
σ_t			1.8130***		1.7159***		1.6741***		1.6929***
			(7.06)		(3.69)		(3.59)		(3.64)
$Spread_t$			-0.2645***		-0.2596***		-0.2583***		-0.2590***
			(3.84)		(7.02)		(6.97)		(7.01)
TV_{t-1}			2.8579***		3.3314***		3.5685***		3.4987***
			(4.00)		(4.86)		(5.10)		(5.07)
N	71,289	71,289	71,123	71,289	71,123	71,289	71,123	71,289	71,123
R^2-adj	0.90%	0.74%	1.51%	0.94%	1.69%	0.94%	1.68%	1.11%	1.71%

Table 9: **Panel regressions: Daily margin trading turnover as dependent variable**

This table reports the regression results of daily margin trading turnover $Margin_t$ on yesterday's return r_{t-1} using panel data. Variables are defined in Table 7. We take the first difference of $Margin_t$, $oimb^-$, σ, $Spread$, and TV due to the unit root in the time series. The standard errors take into account clustering by calendar date and by stock (Thompson, 2011). T-statistics are reported within parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.0177	-0.0344*	0.0204	0.0194	-0.0037	0.0130	-0.0119	-0.0335*	-0.0048
	(1.06)	(1.72)	(1.17)	(1.16)	(0.18)	(0.76)	(0.57)	(1.69)	(0.24)
r_{t-1}	0.0473***		0.0446***	0.0415***	0.0241**	0.0487***	0.0312***	0.0271***	0.0245**
	(6.36)		(5.19)	(5.64)	(2.48)	(6.54)	(3.01)	(3.08)	(2.51)
$Sell^{MA}$				-0.1276**	-0.1886***			-0.1371**	-0.1868***
				(2.16)	(2.91)			(2.32)	(2.93)
Buy^{MA}				0.0973**	0.0518			0.0825*	0.0522
				(2.01)	(1.06)			(1.69)	(1.07)
$Sell^{TRB}$						0.0792	0.0371	0.0578	0.0174
						(1.27)	(0.57)	(0.94)	(0.27)
Buy^{TRB}						0.1175	0.0313	0.1037	0.0435
						(1.00)	(0.27)	(0.89)	(0.37)
$Loser$		-0.0147			-0.0034		-0.0061	0.0481	-0.0034
		(0.55)			(0.11)		(0.19)	(1.58)	(0.11)
$Winner$		0.2889***			0.1635***		0.1613***	0.2114***	0.1632***
		(8.46)			(4.34)		(4.26)	(5.64)	(4.33)
r_t			-0.0630***		-0.0632***		-0.0631***		-0.0632***
			(7.33)		(7.35)		(7.35)		(7.35)
$oimb_t^-$			0.0992		0.1262		0.1235		0.1265
			(1.03)		(1.31)		(1.28)		(1.31)
σ_t			-9.8575***		-9.6687***		-9.5676***		-9.6603***
			(10.14)		(10.04)		(9.84)		(10.05)
$Spread_t$			0.0552		0.0465		0.0452		0.0468
			(0.43)		(0.36)		(0.35)		(0.37)
TV_{t-1}			-1.1510		-1.9456		-2.3093		-2.0009
			(0.68)		(1.16)		(1.36)		(1.19)
N	71,289	71,289	71,122	71,289	71,122	71,289	71,122	71,289	71,122
$R^2 - adj$	0.15%	0.17%	0.83%	0.16%	0.89%	0.15%	0.87%	0.23%	0.88%

Table 10: **Panel regressions: Daily covering of short position or margin position as dependent variable**

This table reports the regression results of daily covering turnover of short-selling positions ($Cover_t^{SS}$) or margin positions ($Cover_t^{MG}$) on yesterday's return r_{t-1} using panel data. Variables are defined in Table 7. We take the first difference of $Cover_t^{SS}$, $Cover_t^{MG}$, $oimb^-$, $oimb^+$, σ, $Spread$, and TV due to the unit root in the time series. The standard errors take into account clustering by calendar date and by stock (Thompson, 2011). T-statistics are reported within parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	$Cover_t^{SS}$					$Cover_t^{MG}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.0036	0.0041	-0.0004	-0.0032	-0.0035	0.0370	0.0389	0.0134	0.0216	0.0330
	(0.66)	(0.81)	(0.07)	(0.56)	(0.68)	(1.52)	(1.61)	(0.48)	(0.74)	(1.21)
r_{t-1}	-0.0025	-0.0025		-0.0094***	-0.0091***	0.0054	0.0053		0.0115	0.0111
	(1.18)	(1.22)		(3.43)	(3.58)	(0.68)	(0.57)		(1.08)	(0.97)
$Down_{t-1}^{MA}$				0.0022	0.0022				-0.0808	-0.0973*
				(0.20)	(0.20)				(1.48)	(1.76)
Up_{t-1}^{MA}				-0.0017	0.0030				-0.0411	-0.0549
				(0.14)	(0.25)				(0.87)	(1.10)
$Down_{t-1}^{TRB}$				0.0382***	0.0348**				-0.0447	-0.0563
				(2.70)	(2.52)				(0.78)	(0.98)
Up_{t-1}^{TRB}				0.0447	0.0381				-0.0008	-0.0172
				(1.35)	(1.12)				(0.01)	(0.19)
$Loser_{t-1}$			-0.0126**	-0.0323***	-0.0298***			0.0825**	0.1106***	0.0913**
			(2.29)	(4.63)	(4.49)			(2.47)	(3.05)	(2.46)
$Winner_{t-1}$			0.0324***	0.0569***	0.0581***			0.0392	0.0098	-0.0084
			(4.78)	(6.13)	(6.36)			(1.58)	(0.29)	(0.27)
r_t		-0.0131***			-0.0131***		-0.0229**			-0.0228**
		(6.22)			(6.32)		(2.10)			(2.08)
$oimb_t^-$		0.0003			0.0104		-0.1128			-0.1180
		(0.01)			(0.45)		(0.80)			(0.84)
$oimb_t^+$		0.0153			0.0062		-0.1643			-0.1482
		(0.37)			(0.15)		(0.87)			(0.79)
σ_t		0.9818***			1.0497***		-3.7108**			-3.6928**
		(3.83)			(4.11)		(2.27)			(2.25)
$Spread_t$		-0.0246			-0.0293		-0.1143			-0.1100
		(0.84)			(1.00)		(0.98)			(0.94)
TV_{t-1}		2.6780***			2.2330***		-2.8082			-2.4388
		(6.75)			(5.92)		(1.52)			(1.36)
N	71,030	70,863	71,030	71,030	70,863	70,637	70,470	70,637	70,637	70,470
R^2-adj	0.01%	0.45%	0.08%	0.23%	0.65%	0.00%	0.10%	0.01%	0.02%	0.11%

Table 11: **Portfolios sorted by short turnover or/and margin turnover**
This table reports average abnormal returns (in bps) for portfolios sorted by short turnover or/and margin turnover. On each day t, we form five portfolios by short turnover change and compute the equal-weighted abnormal returns on day $t+1$. To avoid the impact of bid-ask bounce, we adjust the bid-to-bid return on day $t+1$ by the predicted return from estimating the OLS market model by a rolling window of $[-280, -31]$ trading days, with minimum 180 trading days applied. Then we report the time-series average of those portfolios and the difference in "High" and "Low" short turnover quintiles in Panel A. Panel B is similarly constructed for portfolios sorted by margin turnover change. Panel C is reported for 25 portfolios double sorted first by short turnover and then independently by margin turnover.

Panel A: Portfolio sorted by short turnover							
	Low	2	3	4	High	High - Low	
Mean	-1.648	4.009	2.877	4.315	29.031	30.679	
t-value	-1.52	3.44	1.67	3.72	7.86	7.97	
Panel B: Portfolio sorted by margin turnover							
	Low	2	3	4	High	High - Low	
Mean	8.210	4.029	-0.958	1.039	0.048	-8.162	
t-value	6.08	3.45	-0.64	0.70	0.04	4.30	
Panel C: Portfolio sorted by short turnover and margin turnover							
	Low *Short*	2	3	4	High *Short*	High - Low	*t-value*
Low *Margin*	2.278	6.987	1.468	11.332	56.347	54.068	7.81
2	3.877	5.945	-3.327	2.328	12.814	8.937	1.02
3	-4.492	-0.256	8.835	-1.967	-5.628	-1.136	0.09
4	-1.968	1.156	0.731	2.126	42.060	44.028	3.82
High *Margin*	-8.239	1.704	5.874	6.001	9.737	17.976	2.60
High - Low	-10.517	-5.284	4.406	-5.331	-46.609		
t-value	3.24	1.21	0.84	1.53	5.05		

Table 12: **Panel regression: predicting future returns**
This table reports regression results of future return on day t short, margin, and covering activities, using panel data. AR^{bb}_{t+1} is the bid-to-bid return minus predicted return from the OLS market model, estimated by a rolling window of $[-280, -31]$ trading days, with minimum 180 trading days. $CAR[t+1, t+5]$ is the cumulated abnormal return from $t+1$ to $t+5$ days. Explanatory variables are defined in Table 7. The standard errors take into account clustering by calendar date and by stock (Thompson, 2011). T-statistics are reported within parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	AR^{bb}_{t+1}			$CAR[t+1, t+5]$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0281**	0.0425***	0.0337**	0.1422***	0.1791***	0.1703***
	(2.20)	(2.84)	(2.23)	(3.29)	(3.93)	(3.82)
$Short_t$	0.0347***	0.0301**	0.0219*	0.0280*	0.0159	0.0081
	(2.66)	(2.38)	(1.88)	(1.75)	(1.07)	(0.63)
$Cover^{SS}_t$	-0.0256*	-0.0208	-0.0020	-0.0236	-0.0112	-0.0011
	(1.88)	(1.52)	(0.14)	(1.28)	(0.64)	(0.06)
$Margin_t$	-0.0110***	-0.0104***	-0.0072***	-0.0119**	-0.0101**	-0.0079*
	(3.57)	(3.37)	(2.71)	(2.50)	(2.09)	(1.82)
$Cover^{MG}_t$	-0.0007	-0.0007	0.0006	0.0042	0.0045	0.0057*
	(0.32)	(0.32)	(0.29)	(1.27)	(1.33)	(1.65)
$Down^{MA}_{t-1}$		0.0652**	0.0947***		0.3028***	0.3172***
		(1.98)	(2.77)		(3.34)	(3.63)
Up^{MA}_{t-1}		0.0551	0.0427		0.3257***	0.3292***
		(1.33)	(0.95)		(2.89)	(2.94)
$Down^{TRB}_{t-1}$		-0.1622***	-0.1233**		-0.2948*	-0.2521*
		(2.79)	(2.25)		(1.88)	(1.70)
Up^{TRB}_{t-1}		-0.3332*	-0.3298*		-1.4295***	-1.4641***
		(1.65)	(1.70)		(2.75)	(2.77)
$Loser_{t-1}$		0.0179	0.0400		-0.0098	0.0156
		(0.79)	(1.56)		(0.15)	(0.25)
$Winner_{t-1}$		-0.0765***	-0.0774***		-0.2383***	-0.2178***
		(2.62)	(2.75)		(3.26)	(2.92)
r_{t-1}			0.0066			-0.0037
			(0.75)			(0.18)
r_t			0.0609***			0.0357
			(5.54)			(1.61)
$Spread_t$			-0.0574			0.2432
			(0.57)			(0.88)
$oimb^+_t$			0.0067			0.0067
			(0.74)			(0.74)
σ_t			-0.6621			0.9290
			(0.62)			(0.51)
TV_{t-1}			-6.7012***			0.7385
			(2.96)			(0.16)
N	69,619	69,619	69,461	69,897	69,897	69,734
$R^2 - adj$	0.06%	0.16%	0.97%	0.01%	0.19%	0.24%

Table 13: **Panel regression: Future order imbalance and liquidity**
This table reports the regression results, using day $t+1$ order imbalance and liquidity as dependent variable. Variables are defined in Table 7. The standard errors take into account clustering by calendar date and by stock (Thompson, 2011). T-statistics are reported within parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	$oimb^{-}_{t+1}$		$oimb^{+}_{t+1}$		$Spread_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0077**	0.0159***	-0.0003	0.0058**	0.0002	-0.0021*
	(1.97)	(3.86)	(0.11)	(2.40)	(0.23)	(1.81)
$Short_t$	-0.0052***	-0.0042***	-0.0007	-0.0002	0.0026***	0.0022***
	(4.66)	(4.23)	(0.71)	(0.22)	(3.05)	(2.70)
$Cover^{SS}_t$	0.0026	0.0025	0.0021*	0.0005	0.0021*	0.0025**
	(1.37)	(1.48)	(1.65)	(0.39)	(1.93)	(2.33)
$Margin_t$	0.0022***	0.0020***	0.0013***	0.0010***	-0.0003	-0.0001
	(9.53)	(8.51)	(6.88)	(5.29)	(1.52)	(0.70)
$Cover^{MG}_t$	0.0005*	0.0005	0.0004*	0.0002	0.0002	0.0002
	(1.84)	(1.61)	(1.80)	(1.09)	(0.90)	(1.21)
r_t		0.0010		-0.0068***		0.0016*
		(0.48)		(3.75)		(1.89)
$Down^{MA}_t$		-0.0033		-0.0034		0.0042
		(0.49)		(0.89)		(1.23)
Up^{MA}_t		-0.0237***		-0.0143***		0.0026
		(3.40)		(2.75)		(0.83)
$Down^{TRB}_t$		-0.0078		-0.0030		0.0025
		(1.09)		(0.57)		(0.75)
Up^{TRB}_t		-0.0113		0.0340***		-0.0293***
		(0.86)		(3.06)		(3.33)
$Loser_t$		-0.0065		-0.0196***		0.0021
		(1.55)		(5.74)		(1.00)
$Winner_t$		-0.0259***		-0.0046		0.0076***
		(5.75)		(1.08)		(2.92)
N	70,254	70,254	70,546	70,545	70,239	70,239
$R^2 - adj$	0.31%	1.02%	0.13%	2.22%	0.05%	0.29%

Table 14: **Panel regression: Future volatility**

This table reports the regression results of day $t+1$ volatility measures on day t short, margin, and covering activities, using panel data. Variables are defined in Table 7. The standard errors take into account clustering by calendar date and by stock (Thompson, 2011). T-statistics are reported within parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	$SemiVar^{-}_{t+1}$		$SemiVar^{+}_{t+1}$		$Skew_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.0064	0.0129	-0.0079	0.0191	-0.0004	0.0037*
	(0.34)	(0.76)	(0.40)	(1.08)	(0.30)	(1.84)
$Short_t$	0.0066	0.0024	0.0003	-0.0013	-0.0009	0.0013
	(0.49)	(0.19)	(0.02)	(0.10)	(0.53)	(0.83)
$Cover^{SS}_t$	-0.0266*	-0.0339**	-0.0361**	-0.0478***	-0.0052*	-0.0080***
	(1.85)	(2.37)	(2.25)	(2.98)	(1.93)	(2.87)
$Margin_t$	0.0040	0.0045	0.0066**	0.0061**	0.0008	0.0001
	(1.50)	(1.65)	(2.18)	(2.00)	(1.54)	(0.12)
$Cover^{MG}_t$	0.0086***	0.0079***	0.0106***	0.0095***	0.0009*	0.0007
	(2.89)	(2.73)	(3.01)	(2.77)	(1.67)	(1.27)
r_t		-0.0401***		-0.0575***		-0.0100***
		(4.06)		(5.69)		(7.03)
$Down^{MA}_t$		-0.0029		-0.0097		-0.0108*
		(0.11)		(0.33)		(1.68)
Up^{MA}_t		-0.0246		-0.0057		0.0076
		(0.90)		(0.18)		(1.16)
$Down^{TRB}_t$		-0.0947		-0.1151		-0.0182***
		(0.98)		(1.20)		(2.97)
Up^{TRB}_t		0.1078***		0.1531***		0.0149
		(3.83)		(2.73)		(0.81)
$Loser_t$		-0.1634***		-0.1727***		0.0087**
		(6.36)		(6.46)		(2.46)
$Winner_t$		0.1058***		0.0829***		-0.0211***
		(3.94)		(3.05)		(4.09)
N	70,243	70,243	70,243	70,243	70,243	70,243
R^2-adj	0.05%	0.45%	0.08%	0.65%	0.01%	0.64%

Table 15: **Panel regression: Future efficiency**

We use the cross-autocorrelation coefficient between stock return and lagged market return to measure efficiency. This table reports the regression results of day $t+1$ cross-autocorrelation ρ on day t short, margin, and covering activities, using panel data. Variables are defined in Table 7. The standard errors take into account clustering by calendar date and by stock (Thompson, 2011). T-statistics are reported within parenthesis under the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	ρ_{t+1}		ρ^{-}_{t+1}		ρ^{+}_{t+1}	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.0187	-1.8725***	-0.0386	-1.8990***	-0.0072	-1.9040***
	(0.05)	(4.51)	(0.06)	(3.02)	(0.01)	(3.55)
$Short_t$	0.6945***	0.5233***	0.7418**	0.7590**	0.6509***	0.3122*
	(3.73)	(2.76)	(2.47)	(2.57)	(3.62)	(1.94)
$Cover^{SS}_t$	0.1673	0.1912	0.5994**	0.4069	-0.2744	-0.0382
	(0.76)	(0.89)	(2.17)	(1.49)	(0.85)	(0.12)
$Margin_t$	-0.0131	0.0301	0.0415	0.0301	-0.0667	0.0282
	(0.28)	(0.69)	(0.72)	(0.55)	(0.89)	(0.41)
$Cover^{MG}_t$	-0.1306***	-0.0929**	-0.0960	-0.0757	-0.1644***	-0.1160*
	(3.03)	(2.26)	(1.56)	(1.29)	(2.75)	(1.95)
r_t		0.2904		-0.3568		0.7978**
		(0.92)		(0.74)		(2.05)
$Down^{MA}_t$		-3.9636***		-2.9565**		-5.4024***
		(4.34)		(2.29)		(4.02)
Up^{MA}_t		-3.6740***		-3.7821***		-3.3707**
		(3.97)		(3.27)		(2.39)
$Down^{TRB}_t$		-1.7405*		-2.5501*		-1.0709
		(1.93)		(1.93)		(0.84)
Up^{TRB}_t		-3.1826*		-0.8235		-4.6682
		(1.71)		(0.33)		(1.63)
$Loser_t$		5.3809***		6.8167***		3.9885***
		(7.20)		(6.83)		(3.85)
$Winner_t$		6.4126***		5.0592***		7.6771***
		(7.65)		(4.31)		(6.62)
N	70,542	70,542	33,497	70,542	37,045	70,542
$R^2 - adj$	0.08%	1.90%	0.11%	2.00%	0.07%	3.11%