More Stringent, More Efficient?
Short-Selling Activities and Anomaly Mispricing*

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Abstract

Short-selling in China is not banned but is subject to stringent regulations and oversight. We find that short-selling activities exhibit limited effects on correcting mispricing of anomaly portfolios in the Chinese equity market. While mispricing correction improves in stocks with a high short-selling ratio, it remains insufficient to address mispricing systematically. Two quasi-natural experiments further confirm the above finding. Moreover, we show that informed trading helps reduce mispricing in stocks with a high short-selling ratio; however, excessive informed trading undermines the price discovery function of short-selling. Institutional investors can identify anomaly-implied trading directions, particularly for trading-related anomalies rather than accounting-related ones.

Keywords: Short Selling, Anomaly Portfolios, Institutional Investors, Informed Trading, the Chinese Equity Market

JEL Classification: *G11, G12, G13*

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1. Introduction

Active short selling accelerates information transmission and price discovery, thereby reducing overpricing and improving market efficiency (see, e.g., Miller, 1977; Diamond and Verrecchia, 1987; Boehmer et al., 2013; Boehmer and Wu, 2013). Short-sellers are often considered as informed traders who hold negative information on asset prices and actively short sell to avoid downside risk (Bris et al., 2007; Boehmer et al., 2008; Blau and Pinegar, 2013; Boehmer et al., 2020). However, most of the evidence originates from developed markets. Short-selling in China is not banned but is subject to stringent regulations and oversight. It is part of China's efforts to integrate to global financial markets while maintaining stability with a more cautious approach. In March 2010, the China Security Regulatory Commission (CSRC) launched a pilot scheme, which allows 90 constituent stocks in Shanghai and Shenzhen exchanges to be short sold. Over time, the number of designated stocks increases, and now nearly half of stocks listed in the Chinese main board are eligible for short selling.

However, the short-selling volume remains significantly lower than the margin-buying volume. As shown in Panel A of Figure 1, short-selling balances account for only less than 1% of margin-buying balances. Furthermore, short-selling has still been highly constrained until March 2020, as evidenced in Panel B of Figure 1.[1] This persistent discrepancy between short selling and margin buying reveals a long-standing unilateral

[1]For instance, the 2015 stock market crash in China brought significant attention to short-selling practices. During the crash, the government took immediate actions of implementing short-selling bans and halting trading in a large number of stocks to stabilize the market. In the aftermath of excessive market volatility, regulations were adjusted to strike a balance between allowing flexibility for market activities and preventing destabilizing practices. For more discussions on the market regulations, please see: https://www.economist.com/buttonwoods-notebook/2015/07/03/arent-markets-manipulated-on-the-way-up (accessed on July 3, 2015) and more recent release https://www.reuters.com/markets/asia/china-regulator-unveils-more-curbs-short-selling-2024-02-06/ (accessed on February 6, 2024).

trading pattern in China, whose pricing implications remain underexplored.

[Figure 1 about here]

In this paper, we implement a comprehensive examination of the effects of short selling on mispricing correction for representative anomaly portfolios in China. Focusing on all Chinese A-share stocks for the period ranging from March 2010 to June 2022, we construct 70 representative anomalies, following the literature (e.g., Green et al., 2017; Liu et al., 2019; Leippold et al., 2022; Hou et al., 2023; Li et al., 2024). These anomalies can be categorized into six groups: investment, past returns, profitability, risk, trading friction, and value. To effectively assess the policy impact on mispricing correction, we implement propensity score matching (PSM) analysis to pair each designated stock with an undesignated one that matches similar trading characteristics and serves as a control stock. We form decile portfolios both in the treated and control stocks for each anomaly and create six representative anomaly portfolios as the equal-weighted average of individual anomaly portfolio returns in each category. The six representative anomaly portfolios are taken as our main test assets.

Our findings can be summarized as follows. First, we find that short-selling activities have limited effect on mispricing correction for anomaly portfolio returns in China. Although anomaly returns are lower in the treated stocks than in the control stocks, the return declines are not statistically significant at the level of 5% in all the six categories. Controlling for the market factor (CAPM) or the China four risk factors (LSY-4) of Liu et al. (2019), the difference-in-difference (DiD) test reinforces this baseline result. We further find that alleviation of anomaly mispricing mainly concentrates on stocks with a high short-selling ratio. For example, the number of long-short anomaly portfolios with a significantly positive CAPM alpha decreases from 23 in stocks with a low short-selling

ratio to 15 in stocks with a high short-selling ratio, and the average alpha decreases from 0.45% per month in stocks with a low short-selling ratio group to 0.37% per month in stocks with a high short-selling ratio group. Overall, despite the decrease of mispricing with respect to the increase of the short-selling ratio, a non-negligible amount of mispricing remains in the Chinese equity market.

Second, taking two exogenous shocks as quasi-natural experiments, we confirm the above finding. The first is a positive shock, i.e., the expansion of the short-selling refinancing program. This event remarkably increased shares to be lent in the capital market from September 2013 to May 2015. Throughout this period, the risk-adjusted returns in the treated stocks consistently decrease relative to the control stocks in the six categories, albeit to a limited extent. Nevertheless, we find that the trading-related anomalies exhibit a significant improvement. In contrast, the second shock involves a trading regulation introduced to curb short-selling activities. Responding to the stock market crash in June 2015, the CSRC imposed a ban on the "*t+0*" trading rule to short-selling activities in August 2015, which sharply reduced short-selling volume to less than 33 million shares in two months (see Figure A1). Compared to the first event, we document that the risk-adjusted returns in the treated stocks increase relative to the control stocks due to this regulation intervention.

Third, mispricing correction is more pronounced in stocks with a high short-selling ratio, coupled with a high level of informed trading. We sort the treated stocks into quartile portfolios based on informed trading in each of the three groups on the basis of the short-selling ratio. When informed trading is more intensive, we find that the difference of anomaly returns between the high and low short-selling ratio groups is even higher. This highlights the role of informed trading in short-selling activities as a potential

price discovery mechanism. However, too extreme informed trading, representing a large heterogeneous belief between institutional and retail investors, hurts pricing efficiency. In addition, we show that institutional investors, who are often considered as informed traders and short sellers, trade in proper trading directions in the trading-related anomalies rather than in the accounting-related anomalies. Furthermore, the subsample tests reveal that mispricing correction concentrates on stocks characterized by weak corporate governance and poor information environments. In contrast, ownership structure (SOE vs. non-SOE) does not make a difference to short-selling's effect on mispricing correction.

Finally, we develop a theoretical framework by extending the model of Hong and Stein (2003) for explaining the main empirical findings. Three types of investors involve in the price determination process: a retail investor, an institutional investor, and a risk-neutral arbitrageur. We explicitly introduce the short-selling restriction in China. The model predicts that the short-selling relaxation can reduce overvaluation to a large extent; more importantly, it predicts that under stringent short-selling constraints (such as in China), the equilibrium price could largely diverge from the fundamental value if the level of the heterogeneous belief between the retail and institutional investors is too large. Only when the heterogeneous belief is maintained at a reasonable level, informed trading by the institutional investor helps the equilibrium price converge to the fundamental value.

Our paper closely relates to works that examine the effect of short-selling on pricing efficiency. Chu et al. (2020) document that the short-selling pilot scheme effectively alleviates anomaly mispring in the short-leg portfolios in the US market. Our study complements their findings with the opposite evidence in the Chinese equity market and further reveals the driving mechanisms. In addition, on one hand, contrary to the existing literature that finds improved pricing efficiency from short-selling and margin-trading in

China, we find a limited effect of this market-oriented policy on mispricing correction. Besides, these literature only focuses on individual stocks rather than anomaly portfolios. For instance, extending from the price discovery form short-selling restrictions in the Hong Kong market by Chang et al. (2007), Chang et al. (2014) is the first to document that pricing efficiency of designated stocks increases through intensified short-selling activities in the early stages of the reform. However, Chen et al. (2023) find that improved pricing efficiency of short selling only stem from the combined effect of both relaxed price limit constraints and short-selling activities in the GEM (Growth Enterprises Market) board. Furthermore, Wang et al. (2024) also investigates the deregulation effects of short-selling constraints in China but the findings mainly focus on corporate bond market. On the other hand, we extend the implications of institutional investors' trading on pricing efficiency in China. Tan et al. (2023) suggest that only large retail investors and institutional investors in China trade on relevant information and correctly predict future price movements. Qiao (2024) document that sell-side investors in China actively detect mispricing of anomalies. We extend how their trading in China is related to pricing efficiency within the context of short-selling constraints, and particularly partition institutional investors' trading activities into accounting-based and trading-based anomalies. Overall, to our knowledge, our study provides the first comprehensive examination of the effect of short-selling on mispricing of anomaly portfolios in China.

The remainder of this paper proceeds as follows. Section 2 provides the institutional background of short selling in China and presents sample construction for empirical analyses. Section 3 presents our main empirical findings. Section 4 provides some possible explanations and additional analyses. Section 5 builds a theoretical framework explaining main empirical findings. Finally, Section 6 concludes the paper.

2. Institutional Background and Data

2.1. Short Selling in China

On March 31, 2010, the CSRC launched a pilot scheme allowing stocks to be bought on margin or sold short. Initially, the program covered only 50 constituent stocks of the SSE 50 index and 40 constituent stocks of the SZSE 40 index. The list was then substantially expanded to include 278 constituent stocks of the SSE 180 index and the SZSE 100 index on December 5, 2011. Proceeding with caution and prudence, the regulatory agency conducted three subsequent major revisions, increasing the number of designated stocks to 900 by 2014. Since then, the CSRC further refined the trading rules to accommodate market development. After 2016, the two exchanges performed routine quarterly adjustments, typically adding or removing a small number of stocks from the designated lists. With aims to improve the price discovery process and market liquidity, by August 2019, the total number of designated stocks reached 1,600, covering almost half of all stocks listed on the main A-share boards. As shown in Table 1, seven major revisions have occurred since the pilot program. Each revision introduces a significant increase in the number of designated stocks, ultimately covering nearly half of composite stocks in the main boards.

[Table 1 about here]

Despite these efforts to facilitate short selling and margin trading, transaction costs remain high in China (Chang et al., 2014).[2] In addition, short-selling policy operates un-

[2]For instance, the 28-day refinancing rate-i.e., the annualized borrowing fee that the China Securities Finance Corporation (CSF) charges brokerages when lending stocks-currently centers around 3.5%. See, http://www.csf.com.cn/publish/main/1009/1011/1014/index.html (assessed by CFS). This is more than twice the roughly 1.5% annual borrowing fee observed in global equity lending markets (Muravyev et al., 2025).

der strict regulatory supervision to ensure financial stability and protect retail investors. For example, when turmoils arise, the Chinese government occasionally bans or restricts short selling activities. Consequently, while limits-to-arbitrage have been relaxed for designated stocks, the extent to mispricing correction remains an empirical question, which this study aims to address.

2.2. Data

2.2.1. Sample Selection

Our sample stocks include both designated stocks and non-designated stocks listed on the main board of the Shanghai and Shenzhen stock exchanges and the boards of GEM (Growth Enterprises Market) and STAR (Science & Technology Innovation). The sample period spans from March 2010 to June 2022, with 148 months in total, covering the beginning of the pilot scheme. The designated stocks must satisfy certain requirements regarding market capitalization, turnover rate, and trading volume, and the list is regularly adjusted by the Shanghai and Shenzhen stock exchanges. The detailed requirements are displayed in Table A1. The monthly lists of designated stocks are obtained from CSMAR.[3]

Following Liu et al. (2019), we apply several filters to the data: i) excluding stocks listed less than 6 months; (ii) excluding stocks with less than 120 trading records in the past 12 months or fewer than 15 trading records in the past month; (iii) keeping the largest 70% stocks based on monthly market capitalization to alleviate the shell-value

[3]The Shanghai and Shenzhen Security Exchange regularly release lists of designated stocks. On the last trading day of month t, if the pilot stock is (not) included in the list, we identify the status as "designation (non-designation)" in month t. Few pilot stocks occasionally go through multiple entries and exists. In our sample set, minimum existing days of a designated stock is 34 days, meeting our portfolio management of one-month holding period requirement. We only keep stocks with consistent status, which means that the stock is (not) included in the list at month t, and also (not) in the list at month $t+1$.

issue. Following the recent literature on market anomalies (see, e.g., Green et al., 2017; Leippold et al., 2022; Hou et al., 2023; Li et al., 2024), we construct a broad set of 70 single-sorted anomalies based on representative firm characteristics.[4] In general, these 70 anomalies fall into six categories: risk, investment, past return, profitability, trading friction, and value. While investment, profitability, and value groups are classified as the accounting-related anomalies, risk, past return, and trading friction are regarded as the trading-related anomalies (Hou et al., 2023). More than two thirds of the sample anomalies belong to the categories of profitability and value, and each of the other four categories takes less than 10%. Trading data and stock returns are from WIND, and accounting data and risk-free rate are obtained from CSMAR. Detailed definitions and categories are shown in Table A2 and Table A3, respectively.

2.2.2. Treated and Control Stocks

To examine the effect of the short-selling scheme on pricing efficiency, we implement the propensity score matching (PSM) method to pair each treated stock with a specific control stock. The control stocks are chosen from the sample stocks that have not been included in the lists, and the unpaired stocks are then classified as the untreated stocks. Following the guidelines in Table A1, we choose three matching characteristics: outstanding market capitalization, turnover rate, and trading amount. At the end of each month, for each treated stock, we choose the corresponding control stock from the ineligible stocks with characteristics most similar to the treated stock without replacement.[5] We allow stocks

[4]To exclude the effect of size on anomaly returns, we also form the 2×3 double-sorted portfolio returns. These anomalies are formed by sorting on the size median across the whole sample stocks, and then sorting on 30th and 70th percentile breakpoints of each firm characteristic. The empirical results are similar. Directions of long-short positions ensure that the average returns of each long-short decile portfolios remain positive.

[5]The sampling with replacement is implemented as the robustness test, and the empirical results are similar. We also use the average magnitudes of matching characteristics over the previous three months as the robustness test, and the empirical results are similar.

added to the list later to be selected as controls for stocks added to the list earlier in the sample period (Wan, 2020).

Panel A of Table 2 shows that the average differences in matching characteristics between the treated and control stocks are consistently smaller than those between the treated and untreated stocks. Specifically, the mean difference between the treated and control stocks (treated and untreated stocks) in the log of market capitalization, turnover, and trading amount are -0.82 (-1.25), 0.27 (0.33), and -0.55 (-0.91), respectively. Overall, our analysis suggests that the PSM approach yields a reliable estimate of the policy effect on stock prices. Thus, we conclude that the distinction of anomaly patterns between treated and control stocks is mainly driven by the implementation of the short selling policy. Figure A2 in the Internet Appendix displays the time-series observations of both treated and control stocks in the four boards.

To create characteristic-based anomaly returns, we form decile portfolios based on each characteristic in month t, and calculate their value-weighted portfolio returns in month $t+1$. For each characteristic, the long-short investment strategy goes long the portfolio that earns the highest returns (long leg) and shorts the portfolio that earns the lowest returns (short leg).[6]

3. Empirical Results

In this section, we empirically investigate the impact of short-selling on anomaly mispricing in the Chinese equity market.

[6]The long-short direction of each investment strategy is consistent with that of sorting results from full sample including both treated and control stocks. For portfolios constructed from treated stocks, we require at least 50 individual stocks in each portfolio per month.

3.1. The Risk-Adjusted Returns

To start with, we first construct 70 single-sorted anomaly portfolios across the following three set of stocks: i) the treated stocks with the short-selling qualification, ii) the control stocks without this qualification, and iii) the combination of both the treated and control stocks. Categorizing 70 individual anomalies into six groups, we form the "representative anomaly" by calculating the equal-weighted returns across individual anomalies in each category for the three sets of stocks. Compared with individual anomalies, the representative anomaly largely diversifies away the idiosyncratic component in each category.

Panel B of Table 2 presents summary statistics of the long-short representative anomalies. The monthly average returns and volatility of anomalies in the treated stocks are in general lower than those in the control stocks in the five categories, except for the category of risk. This suggests that the relaxation of short-selling could alleviate mispricing to a certain extent. For example, the value group in the control stocks exhibits the highest monthly excess returns of 0.98% with the standard deviation of 2.84% (Panel B.1); in contrast, in the treated stocks, it generates a smaller average return of 0.68% and a lower volatility of 2.65% (Panel B.2). When we combine both the treated and control stocks, average returns and volatility of anomalies are between those of the treated and control stocks (Panel B.3).

[Table 2 about here]

To disentangle mispricing from systematic risk, we rely on two commonly used factor models, CAPM and the four-factor model of Liu et al. (2019) (LSY-4), to calculate anomaly alphas. The LSY-4 model accounts for the shell-value issue in the Chinese equity market and is regarded as a benchmark model. It includes a market factor (MKT), a size

factor (SMB), a value factor based on the earning-to-price ratio (VMG), and a sentiment factor based on turnover (PMO). We first obtain the risk-adjusted alpha for each of the 70 anomaly portfolios and then compute the equal-weighted average alphas in each category.

We find that in contrast to the evidence of the impacts of short-selling on correcting anomaly mispricing in developed countries (see, e.g., Chu et al., 2020), the evidence in China is much weak. As shown in Panel A of Table 3, although the anomaly alphas in the treated stocks are reduced relative to those in the control stocks, the decrease in mispricing is not statistically significant at the significance level of 5%. Taking the profitability category as an example, the CAPM (LSY-4) alpha in the treated stocks is about 0.35% (0.44%) per month, which is lower than that in the control stocks. However, the decreasing magnitude, which is -0.14% (-0.19%), is statistically insignificant and economically unsubstantial. This evidence suggests the limited impact of short-selling on mispricing correction for anomaly returns in China. We also check mispricing corrections in long and short legs of anomaly portfolios in Panels B and C, respectively, and the empirical results are similar.

[Table 3 about here]

3.2. The Regression Analysis

To further examine mispricing correction of short selling to anomaly returns, we design a difference-in-difference (DiD) test that controls for unobserved factors potentially affecting asset prices. Specifically, we regress the representative anomaly returns of long-short, long-leg, and short-leg portfolios on a dummy variable, $\text{Treat}_{j,t}$, which equals 1 if the

anomaly is constructed from the treated stocks and zero otherwise:

$$r_{j,t+1} = \beta_0 + \beta_1 \text{Treat}_{j,t} + \beta_2 \text{Risk factors}_{t+1} + \gamma_{t+1} + \varepsilon_{j,t+1}, \tag{1}$$

where $j = 1, 2, \cdots, 6$ represent the six categories, and Risk Factors$_{t+1}$ control for the systematic risks. We include LSY-4 factors to proxy for systematic risks. The year fixed effects, γ_{t+1}, are also controlled. Because our sample period covers all revision events since the pilot scheme, Treat$_{j,t}$ can be essentially regarded as an interaction term. The mispricing component is given by $\alpha_{j,t} = \beta_0 + \beta_1 \text{Treat}_{j,t}$, capturing the policy effect. Consistent with the risk-adjusted results in Table 3, Table 4 shows that the coefficient of β_1 is negative in most categories, but statistically insignificant at the significance level of 5%. This finding further confirms the limited effect of short selling on mispricing correction in the Chinese equity market.

[Table 4 about here]

In addition, we run the monthly Fama-MacBeth regression (Fama and MacBeth, 1973) for future individual stock returns in Eq.(2) for a robustness check,

$$r_{i,t+1} = \beta_0 + \beta_1 \text{Treat}_{i,t} + \beta_2 \text{Controls}_{i,t} + \varepsilon_{j,t}, \tag{2}$$

and we find that the coefficient, β_1, is negative but statistically insignificant. Detailed regression results are presented in Table A4 in the Internet Appendix.

3.3. Effects of the Short-Selling Ratio

Thus far, we have found a limited impact of short-selling on mispricing correction. However, given the frequent government interventions on short selling in China, the enhanced

pricing efficiency due to the short-selling relaxation may exist only in stocks with a high short-selling ratio. Intuitively, a designated stock with a high short-selling ratio, which contains more negative beliefs of investors, is likely to have a lower future return (Boehmer and Wu, 2013; Boehmer et al., 2013). For each designated stock, CSMAR provides the detailed quantity of shares that have already been borrowed and sold through the short-selling activities on each trading day. We then proxy the short-selling ratio for a treated stock as the total daily shares that are borrowed and sold, scaled by the total A-share outstanding within a month.

We first sort the treated stocks into three portfolios based on the short-selling ratio at the end of each month, and the top 30%, medium 40%, and bottom 30% stocks are classified as the high, medium, and low short-selling ratio portfolios. One notable event is that, during the period from August 2015 to April 2016, the ban on "*t+0*" trading rule was effective. This result in approximately 50%-70% treated stocks in our sample with zero shorting demand. Hence, for this period, we define the treated stocks with zero short-selling ratio as the low short-selling ratio group, and split the remaining stocks into the medium and high short-selling-ratio groups based on the median value. Within each short-selling ratio group, the treated stocks are then sorted into deciles based on each of 70 characteristics. Finally, we calculate the one-month-ahead value-weighted portfolio returns.

Panel A of Table 5 reports the average return (average alpha) and the number of long-short anomalies that generates statistically significant returns (alphas) in each short-selling-ratio group. We find that mispricing in stocks with the low short-selling ratio is more serious than in stocks with the high short-selling ratio. For example, after adjusting for the LSY-4 risk factors, in the group with the low short-selling ratio, 46 anomalies

generate positive alphas, among which 22 are statistically significant at the significance level of 10%. In contrast, in the group with the high short-selling ratio, the number of anomalies that generates positive alphas decreases to 38, among which only 18 are statistically significant at the significance level of 10%. Consistently, when comparing the monthly average alpha of all 70 anomalies in each short-selling-ratio group, the average alpha in the low short-selling-ratio group is much higher than in the high short-selling-ratio group, 0.37% vs. 0.24%.

[Table 5 about here]

For robustness checks, Panels B and C of Table 5 report results for long- and short-leg portfolios. Notably, we find that mispricing correction to the stocks with the high short-selling ratio is much stronger in the short-leg portfolios than in the long-leg portfolios. The number of the short-leg portfolios that generate statistically significant returns/alphas in the high short-selling ratio group is almost zero. Moreover, we note that the monthly average risk-adjusted return (CAPM or LSY-4 alpha) in the high short-selling ratio group becomes negative, suggesting that the overvaluation in stocks with the highest short-selling pressure is diminished, thereby generating declining future expected returns.

Taken together, the above evidence suggests that the relaxation of short-selling constraints can improve pricing efficiency by mitigating overvaluation in China. However, this effect appears to be limited to designated stocks that are subject to a high level of short-selling pressure, still leaving considerable mispricing in the Chinese equity market.

3.4. Two Natural Experiments

3.4.1. Natural experiment I: The short-selling refinancing policy

We employ the short-selling refinancing policy as one of the natural experiments to clearly disentangle the effect of short selling on mispricing correction. This event exogenously increases the shares to be lent and thus temporarily alleviates short-selling restrictions in the equity market. Therefore, it provides a natural experiment to examine the impact of short-selling on anomaly mispricing. Although considerable efforts have been made to relax short-selling restrictions since 2010, the shares that can be lent in the capital market remain insufficient. To further address this issue, the CSRC approved the China Securities Finance Corporation (CSFC) to launch the short-selling refinancing policy in February 28, 2013. This policy allowed CSFC to borrow shares from institutional investors and other lenders, and then lend them to securities firms for their clients to short sell, eventually expanding the availability of shares for short selling. As shown in Figure A3 in the Internet Appendix, the amounts of shares to be lent and the transaction volume increase dramatically over the period from September 2013 to May 2015. However, this policy was suspended after the stock market crash in August 2015.[7] We implement similar empirical analyses to those in Section 3.1 for the period from September 2013 to May 2015.

Panel A of Table 6 presents (risk-adjusted) returns of the representative anomalies both for the treated and control stocks in the six categories. Largely consistent with our previous findings, the (risk-adjusted) returns of anomalies portfolios in the treated stocks are lower than that in the control stocks. Notably, for two trading-related categories,

[7] After three enlarging phrases in September 16, 2013, June 20, 2014, and April 30, 2015, the number of refinancing stocks gradually increase and cover the list of designated stocks. For regulation details, see, for example, https://www.moj.gov.cn/pub/sfbgw/flfggz/flfggzbmgz/201203/t20120328_145131.html (in Chinese, accessed on March 28, 2012).

i.e. risk and trading friction, the CAPM alpha differences between treated stocks and control stocks are statistically significant. Moreover, the LSY-4 alpha difference in the risk category is statistically significant at the 1% level. However, the return differences, especially for three accounting-related anomalies, are not statistically significant, suggesting negligible impact of short selling on correcting mispricing among accounting-related anomalies. This reveals that the relaxation of short-selling constraints enhances pricing efficiency particularly for anomalies associated with types of risk and trading friction.

[Table 6 about here]

3.4.2. Natural experiment II: The ban on "t+0" trading rule

Contrary to the expansion of short-selling of the above event, we examine the effect of a unique negative regulation shock on mispricing correction, i.e., the ban on "*t+0*" trading rule. To curb extreme market volatility and prevent sudden declines in stock prices in the aftermath of the stock market crash in June 2015, the CSRC imposed a ban on the "*t+0*" trading rule, and then replaced with the "*t+1*" rule on August 3, 2015. The ban on "*t+0*" trading rule aims to prevent short sellers from using short sales to engage in intraday trading.[8] Consequently, the major state-owned security firms were regulated not to lend out shares and their short-selling accounts were suspended, leaving only smaller security firms capable of constrained short selling activities. Approximately, this regulation shock lasts from August 2015 to April 2016, resulting in a notable drop in short-selling balance in the whole market.

[8]For example, investors who have sold securities on credit (securities lending) are now required to start repaying the borrowed securities to the securities company through direct return of securities or buy-back from the next trading day. The new rule also prevented some investors from using the securities lending service to indirectly conduct intraday round-trip trading. For more detailed regulations, please see: http://www.sse.com.cn/services/tradingservice/margin/edu/c/c_20161025_4192521.shtml (in Chinese, accessed on October 25, 2016).

We implement very similar empirical analyses to the first natural experiment. Panel B of Table 6 shows that more than half categories of the representative anomalies exhibit higher (risk-adjusted) returns in the treated stocks than that in the control stocks. For example, the LSY-4 alpha differences between them are positive for all the categories except the category of trading friction. The risk anomaly, which exhibits a pronounced response to the policy regulation identified in the first natural experiment, shows a significantly positive CAPM alpha at the 1% level.

Overall, relying on two exogenous shocks representing expansion and retraction of short-selling activities, we further provide solid evidence of the effect of short-selling on anomaly mispricing correction; however, such evidence is weak. When the policy constraints on short-selling become lenient, the pricing efficiency improves for designated stocks, albeit to a limited extent. Interestingly, it seems that trading-related anomalies appear to be more sensitive to these policy shifts than accounting-related anomalies.

4. Further Analyses

In this section, we further investigate the effect of short selling from the perspectives of informed trading and arbitrage activities of institutional investors. Subsample tests are also examined based on the unique institutional background in China.

4.1. Informed Trading and Institutional Investors

4.1.1. Informed Trading

Short-sellers are often considered as informed traders that privately own negative information.[9] The literature shows that the active trading behavior driven by the heteroge-

[9]Theoretical and empirical evidence on informed trading of short-sellers, see, e.g.,Verrecchia (1982); Diamond and Verrecchia (1987); Christophe et al. (2010); Blau and Pinegar (2013); Boehmer et al. (2008,

neous belief is particularly prominent among informed trading (Harrison and Kreps, 1978; Wang, 1998; Brockman and Chung, 2000). Therefore, the combination of short-selling constraints and a certain level of informed trading would theoretically correct mispricing. Following Easley et al. (2002) and Easley et al. (2012), we use the level of informed trading, VPIN, as the proxy for informed trading. The data are from CSMAR. In the three groups based on the short-selling ratio formed in Section 3.3, we further sort the treated stocks into quintile portfolios on the basis of informed trading. We then compute the value-weighted excess returns and CAPM-adjusted alphas of these portfolios.

Several findings are worth noting. First, consistent with previous evidence, the short-selling ratio effectively mitigates overpricing, as it negatively predicts future returns. As shown in the last column of Table 7 (Ucon.(SSR)), both excess returns and CAPM-adjusted alphas monotonically decrease with an increase of the short-selling ratio. The long-short (low-minus-high) strategy generates an average excess return (CAPM-adjusted alpha) of 0.75% (0.80%) per month, which is highly statistically significant at the level of 1%. Second, and more importantly, a relatively high level of informed trading strengthens the negative relationship between the short-selling ratio and future expected returns. The return spread based on the short-selling ratio monotonically increases with respect to informed trading (row "LMH (SSR)"), and remains consistently significant at the level 5% within a certain level of informed trading. For example, in the low informed-trading group (column "2"), the return (alpha) spread between the low and high short-selling ratio portfolios is 0.82% (0.84%) per month, while it increases to 0.90% (0.97%) per month in the high informed-trading group (column "4").

[Table 7 about here]

2013, 2020).

However, we notice that the effective price discovery suddenly disappears for the extremely high informed-trading group (column "5"). One possible explanation is that extremely high informed trading squeezes out uninformed investors to trade against informed investors. To avoid possible losses, uninformed investors adversely exit the market (Easley et al., 2011; Wan, 2020), leading to substantial decreases in market liquidity. Therefore, this explains that under a market condition with an extreme lack of liquidity, the short-selling ratio cannot eliminate mispricing of anomaly returns.

Under stringent short-selling constraints in China, mispricing correction is more evident only for a moderate level of informed trading. As is shown in Table 7, negative relationship is more evident when informed trading is constrained below group 5 and above group 1. In other words, mispricing may not be corrected at a too low or too high level of informed trading.[10]

4.1.2. Participation of institutional investors

Institutional investors, equipped with their sophisticated skills (Huang et al., 2020), also act as short-sellers and informed traders, thus playing a crucial role in mispricing correction (D'avolio, 2002; Nagel, 2005; Birru et al., 2024). Gao and Wang (2023) find that US mutual funds actively trade in anomaly-implied directions, which is further confirmed in recent studies that examine the link between quant investing and anomaly patterns (Birru et al., 2024).

We then investigate whether institutional investors in China trade in the proper direction implied by anomalies. We proxy the participation of institutional investors as the

[10]To rule out the potential mixing effect of margin-trading activities on mispricing correction, we replace the short-selling ratio with margin-trading ratio, and then perform the same procedure. However, no evidence suggests that margin-trading activities accelerate price discovery process. Results are available upon request.

quarterly ratio of the market value of shares held by institutional investors to the outstanding market capitalization of A-shares. The data are obtained from WIND, which provide an accurate measure of ownership by mutual funds, security firms, insurance companies, and banks.[11] In terms of anomaly-implied trading direction, we first obtain the decile rank score of individual stocks for each individual anomaly at the end of each month and then calculate the equal-weighted average of rank scores in each anomaly category. The variable of the anomaly-implied trading direction, $\text{Trade}_{i,t}$, equals 3 (1) if the average rank score is higher (lower) than the top 90% (bottom 10%) percentile in each month, and 2 otherwise. Thus, a lower value of the trading direction variable is associated with more evident shorting preference. We also include an interaction term with the short-selling ratio, $\text{SSR}_{i,t}$ to analyze the effect of short-selling on the trading preference of institutional investors.

The stock-level regression on the designated stocks in each category runs as follows,

$$\begin{aligned} IO_{i,t} = \beta_0 + \beta_1 \text{SSR}_{i,t} + \beta_2 \text{Trade}_{i,t} + \beta_3 \text{SSR}_{i,t} * \text{Trade}_{i,t} \\ + \beta_4 \text{Controls}_{i,t} + \gamma_t + \delta_i + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where $\text{IO}_{i,t}$ represents institutional ownership of stock i in month t, and control variables and firm and month fixed effects are included. The positive β_2 suggests that institutional investors trade in the right direction implied by anomalies. In addition, if both β_1 and β_3 are negative, this suggests that institutional investors, who are more informed of negative information with sophisticated skills, reduce their exposure to stocks with a high short-selling ratio to avoid potential losses.

Consistent with evidence that increased short-selling activities contain negative infor-

[11] These entities are distinctly classified from industrial capital, government shareholdings, controlling individual shareholders, and general retail investors in China. Therefore, they are recognized as sophisticated institutional investors who timely provides trading liquidity.

mation on future returns, institutional investors decrease their holdings in stocks with a high short-selling ratio (Nagel, 2005; Boehmer et al., 2013; Boehmer and Wu, 2013). As shown in Column (1) of Table 8, the coefficient β_1 is significantly negative at -6.27 (t = -7.31). Additionally, all the interaction terms with the short-selling ratio, β_3, in all categories in Table 8 generally turn negative.

[Table 8 about here]

Furthermore, in terms of mispricing correction, Chinese institutional investors appear to more effectively engage in trading-related anomalies than in accounting-related anomalies. As discussed before, this trading behavior may explain the notable reduction in abnormal returns associated with trading-related anomalies when a large amount of shares can be lent in Table 6. Column (3), (5), (6) of Table 8 show that the coefficients on the trading direction in trading-related anomalies, such as past returns, risk, and trading friction, are all significantly positive at the level of 5%. This is in sharp contrast to the counterparts in accounting-related anomalies, which are all statistically insignificant. In addition, we find that the interaction terms with respect to the short-selling ratio are negative and statistically significant in the trading-related categories of risk and trading friction.

Moreover, we also investigate asymmetric impacts of both long- and short-leg trading directions as follows,

$$\begin{aligned} IO_{i,t} &= \beta_0 + \beta_1 \text{SSR}_{i,t} + \beta_2 \text{Trade}^{+}_{i,t} + \beta_3 \text{SSR}_{i,t} * \text{Trade}^{+}_{i,t} + \beta_4 \text{Trade}^{-}_{i,t} + \beta_5 \text{SSR}_{i,t} * \text{Trade}^{-}_{i,t} \\ &+ \beta_6 \text{Controls}_{i,t} + \gamma_t + \delta_i + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where the dummy variable for the long-leg (short-leg) trading direction, $\text{Trade}^{+}_{i,t}$ ($\text{Trade}^{-}_{i,t}$),

is set to 1 if the average rank score, $\text{Trade}_{i,t}$, equals 3 (1) and 0 otherwise. Control variables and firm and month fixed effects are also included. If β_2 is positive and β_4 is negative, we then posit that institutional investors trade in the right directions implied by the long- and short-leg anomalies, respectively. This is because a high anomaly rank is associated with an increase in inflows of institutional ownership for the long-leg portfolio, while a low rank is associated with an increase in outflows for the short-leg portfolio.

We confirm that in general, institutional investors accurately trade aligning with both long- and short-leg directions in the trading-related anomalies. Columns (3), (5), and (6) of Table 9 show that in the trading-related anomalies of past return, risk, and trading friction, the long-leg trading directions are all positive and statistically significant. The short-leg trading directions are all negative, and statistically significant at least at the level of 10% except for the category of risk ($\text{Trade}_{\text{Risk}^-}$). Overall, all results show that Chinese institutional investors, who trade actively using their information advantages over retail investors, are able to identify anomaly-implied trading directions in the trading-related anomalies to improve mispricing correction.

[Table 9 about here]

4.1.3. Asymmetric information

The stark contrast between the proportions of retail investors versus institutional investors creates the strong effect of information asymmetry in the Chinese equity market (Ho et al., 2022). Information asymmetry is higher when corporate governance is weaker (Diamond, 1985; Kanagaretnam et al., 2007), thereby increasing incentives for short sellers and informed traders to exploit negative information. The institutional investors with superior information-processing ability short sell relying on their information advantage.

Following Bharath et al. (2009), our measure of stock-level information asymmetry is derived as the first principal component of the liquidity ratio of Amihud et al. (1997), the illiquidity ratio of Amihud (2002), and the absolute magnitude of return reversal of Pástor and Stambaugh (2003). For each of three groups based on the short-selling ratio as in Section 3.3, we sort the treated stocks into quintile portfolios on the basis of the level of asymmetric information. We then compute the value-weighted excess returns and the CAPM-adjusted alphas of these portfolios.

[Table 10 about here]

We find that the negative return predictive power of the short-selling ratio concentrates on stocks with high information asymmetry. In other words, information asymmetry further strengthens the negative relationship between the short-selling ratio and future stock returns. Specifically, in portfolios with a high short-selling ratio, stocks with low information asymmetry outperform stocks with high information asymmetry by 2.38% per month both in excess returns and CAPM-adjusted alphas, whereas in portfolios with a low short-selling ratio, the corresponding outperformance is 2.06% (2.08%) in excess returns (CAPM-adjusted alphas). The return (alpha) spread between the low and high short-selling ratio portfolios increases by 0.75% (0.79%) from low to high information asymmetry. High information asymmetry implicitly reflects the heterogeneous belief of investors in stock prices due to costly information collecting and processing (Wang, 1998; Brockman and Chung, 2000).

4.2. Subsample Analysis

We consider several key features of the Chinese equity market. It has been shown that external short-selling pressure uncovers negative information and exerts a monitoring

effect on firms with weak corporate governance (Callen and Fang, 2015; Jiang et al., 2022). In addition, many Chinese listed firms are under criticism of information manipulation (Titman et al., 2022). Furthermore, given the unique ownership structure of Chinese listed firms, weak corporate governance and information manipulation may be more pronounced in non-SOE firms (Bradshaw et al., 2019). Consequently, anomaly mispricing may be more severe in firms with weak corporate governance, opaque information environment, or non-SOE firms (Hou et al., 2023; Allen et al., 2024). We then investigate the effect of short-selling on mispricing correction in stocks with those features.

We perform three subsample tests. First, we construct a corporate governance proxy using the first principal component of CEO duality, managerial compensation, managerial shareholdings, board size, and ownership concentration (Jiang and Kim, 2015). Second, we measure a firm's information environment using its annual information disclosure rating (see, e.g., Ho et al., 2022): Shanghai and Shenzhen stock exchanges rate listed firms as A (Excellent), B (Good), C (Fair), or D (Poor) based on accounting disclosure quality. We classify firms with A/B ratings as high accounting information quality and those with C/D ratings as low quality. Third, we split all firms into SOE and non-SOE firms by their ownership structure.

We first partition the treated and control stocks into subsamples based on the respective median values of the above three features. We compute 70 long-short decile anomaly excess returns for each subsample and form a "representative anomaly" for each of the six anomaly categories. To ensure sufficient observations for each portfolio, we restrict the subsample period to January 2014-June 2022.

In general, Table 11 shows that the short-selling efficacy in correcting mispricing is stronger in stocks with weak corporate governance and poor information environments.

We see in Panels A and B that firms with weak corporate governance and poor information quality exhibit more pronounced anomaly return differentials between treated and control stocks than those with strong corporate governance and high-quality information environments. We see that for stocks with weak corporate governance, the return difference is negative and statistically significant in the categories of trading friction and profitability. For stocks with poor information environments, the return difference is negative and statistically significant in the category of trading friction. In contrast, the effects in firms with strong governance or high information quality are negligible and statistically insignificant. Panel C reveals less consistent results in the subsample of ownership structure. For example, the short-selling effect is stronger for non-SOE stocks in the category of profitability, whereas it is much stronger for SOE stocks in the category of trading friction.

[Table 11 about here]

5. A Theoretical Framework

In this section, we propose a theoretical model by extending the model of Hong and Stein (2003), and take into account the effects of the short-selling policy in the Chinese equity market. Our analysis typically focuses on market downturns when short-selling constraints prevent investors from revealing their pessimistic beliefs. This is particularly important to understand the determination of equilibrium prices during market crashes and their relationship with the short-selling policy in China (Ni and Yin, 2020; Deng, Gao, and Kim, 2020).

5.1. Model setup

Following Hong and Stein (2003), we assume that there are four trading stages of $t = 0, 1, 2, 3$. At the terminal time, $t = 3$, the stock pays out a definite dividend. The price-setting mechanisms at time $t = 0, 1, 2$ are conducted by the auctioneer, who adjusts the auction price, p_t, based on the trading actions of all the market participants until a market-clearing price is achieved. We assume that three types of market participants engage in the auction process for equilibrium prices. The investors A and B, constrained by the short-selling policy in China, probably conceal their private information if the auction prices are higher than their own belief. The third type of investors is a risk-neutral arbitrageur without short-selling constraints, who freely consumes the excess demand in the market so that the total supply is zero. The market-clearing price cannot be achieved unless the auction price reduces to the proper evaluation of investors A and B because they are more informed than the arbitrageur. Given a large proportion of retail investors in China, we assume that investor A, who is usually more bullish than investor B, represents the behavior of retail investors. Naturally, the behavior of the remaining market players, such as institutional investors, is summarized by that of investor B.

Retail investors are generally less informed compared to institutional investors in China (Titman et al., 2022; Tan et al., 2023). Thus, we denote the heterogeneous belief between investors A and B as H. Let the upper bound of investor B's valuation be $2V$ $(V > 1)$,[12] and set the domain of H to $1 < H < 2V$. This framework has the following economic implications: (i) when the level of the heterogeneous belief, H, is low, the trading behavior of institutional investors aligns with that of retail investors. This is consistent with evidence of the herding behavior of institutional investors in China

[12] V measures the variance of the news that is received by investors, and is the rational expectation of the initial price by investor B (see, Hong and Stein, 2003).

and the subsequent distorted consequences (Li and Wang, 2010; Li et al., 2017; Jiang and Wang, 2024).[13] (*ii*) Conversely, the high level of the heterogeneous belief indicates a substantial information gap between the two types of investors, suggesting that retail investors may be disadvantaged due to lack of investment skills or information asymmetry arising from insider trading (Chi et al., 2022; Chen and Wu, 2022). (*iii*) Therefore, an optimal trade-off can only be achieved when the heterogeneous belief is maintained at a moderate level, at which informed trading can effectively facilitate price discovery.

Our model introduces an important parameter that captures short-selling restrictions in the Chinese equity market. Both investors A and B face short-selling constraints, represented by a positive random variable, ε. A higher value of ε indicates more stringent short-selling constraints implemented by CSRC.[14] This parameter exerts distinct effects on the behavior of different market players. Vulnerable to information asymmetry, e.g., due to inside trading (Chen and Wu, 2022), retail investors tend to maintain irrationally inflated expectations for low-priced stocks. This is consistent with the fact that retail investors show different trading dynamics compared to institutional investors (Tan et al., 2023) and trace for small stocks driven by immediate emotions in China. Therefore, we assume that the price valuation of investor A, denoted by S_A, is uniformly distributed in the interval of $[H\varepsilon, H+2V]$. This indicates that the over-valuation of low-priced stocks is amplified by both the level of the heterogeneous belief H and the short-selling constraint

[13]Specifically, the herding behavior of institutional investors in China is summarized in the following literature. Li and Wang (2010) document that the Chinese institutional investors herd-trade in large stocks and this causes the unexpected high volatility patterns. Li et al. (2017) shows that institutional investors in China also pay attention to the trading styles of retail investors in investment. Recently, Jiang and Wang (2024) finds the distorted behavior of Chinese mutual fund companies in year-end ranking games. Analysis report also show that the trading behavior of institutional investors are at the risk of retail investors in China. See, http://sf.ruc.edu.cn/publish/sf/alk/alfl/jr/86f842bb84b0401ca57873fe1906e971.htm (accessed on September 12, 2020, in Chinese).

[14]Panel A of Figure A4 in the internet appendix shows the increased demand curve considering the short-selling constraints in China, and Panel B of Figure A4 plots the decision tree in the sequential price-setting mechanism.

of ε for retail investors. Likewise, we assume that the price valuation of investor B, denoted by S_B, is uniformly distributed in the interval of $[\varepsilon, 2V]$. Compared to the price valuation of retail investors, the key difference is that the over-valuation of low-priced stocks by institutional investors is only determined by the degree of the short-selling constraint ε.

We suggest a domain of ε as $1 \leq \varepsilon < 1 + 2V/H$,[15] and the condition of $\varepsilon = 1$ serves as a benchmark model. In general, the bounded ε aligns with the initiation of the pilot program on short selling in China since March 2010. Nonetheless, as the short-selling policy evolves over different phases in China, the policy implications remain to be tested both theoretically and empirically.

5.2. Price determination process

At time 0, no investors reveal any private information. Investor B first reveals her private information at time 1, followed by investor A's trading at time 2. Then, we calculate the cutoff prices, at which all the information is revealed precisely.[16] Intriguingly, the final revelation of cutoff prices depends on different levels of short-selling policies, ε, and the heterogeneous belief, H, which eventually converge to two definite values.

At the initial stage of $t = 0$, before neither investor takes any trading action, the equilibrium price reflects the arbitrageur's *ex ante* expectation of the two investors:

$$P_0(\varepsilon) = \frac{E_0(S_A) + E_0(S_B)}{2} = \frac{\left(V + \frac{H(1+\varepsilon)}{2}\right) + \left(V + \frac{\varepsilon}{2}\right)}{2} = V + \frac{H(1+\varepsilon) + \varepsilon}{4}. \quad (5)$$

[15] The Chinese listed firms are regulated to be delisted if the daily closing price is lower than 1 RMB during the latest 20 trading days. Thus, we assume the lower bound of price evaluation higher than 1 RMB for all investors.

[16] For the comprehensive polling outcomes of different price determination process, please refer to Propositions of Hong and Stein (2003).

Given the interval of ε, the equilibrium price, $P_0(\varepsilon)$, converges to two levels,

$$\begin{aligned} \lim_{\varepsilon \to 1+\frac{2V^-}{H}} P_0(\varepsilon) &= \left(\frac{3V}{2} + \frac{1}{4}\right) + \frac{1}{2}\left(H + \frac{V}{H}\right), \\ \lim_{\varepsilon \to 1^+} P_0(\varepsilon) &= V + \frac{2H+1}{4}. \end{aligned} \tag{6}$$

Thus, the equilibrium price strictly increases with the level of short-selling constraints, as shown in Eq. (5). The price is inflated in the case of $\varepsilon \to 1+\frac{2V^-}{H}$ from the fundamental value, with comparison to the benchmark case ($\varepsilon = 1$). An interesting case is when $\varepsilon \to 1 + \frac{2V^-}{H}$, where the equilibrium price depends on the heterogeneous belief H as a U-shaped function. The lowest equilibrium price is achieved at $H = \sqrt{V}$, which strictly falls within the domain of H. When $H > \sqrt{V}$ ($H \leq \sqrt{V}$), the price monotonically increases (decreases) with the value of H. This implies that in the Chinese equity market, under stringent short-selling constraints, in particular, when there exists a relatively high degree of the heterogeneous belief or herding behavior, the equilibrium prices largely diverge from the fundamental value. Conversely, the equilibrium price is closer to the fundamental value at a reasonable level of the heterogeneous belief.

We move on to $t = 1$, when only investor B is involved in the auction process but her private information is concealed. Because of $E_0(S_A) = E_1(S_A) = V + \frac{H(1+\varepsilon)}{2}$, the equilibrium price $P_1(\varepsilon)$ is given by,

$$P_1(\varepsilon) = \frac{E_1(S_A) + E_1(S_B)}{2} = \frac{E_1(S_A) + E_1(S_B \mid S_B \text{ is constrained })}{2}. \tag{7}$$

Following Hong and Stein (2003), we assume that there exists a cutoff value of S_B^*. Clearly, investor B's information is concealed only when S_B is lower than the cut-off value of S_B^*. $E_1(S_B \mid \varepsilon \leq S_B \leq S_B^*)$ is uniformly distributed on $[\varepsilon, S_B^*]$, and thus

$E_1\left(S_B \mid \varepsilon \leq S_B \leq S_B^*\right) = \frac{S_B^* + \varepsilon}{2}$. The auction price will not decrease until the price drops below S_B^*. Therefore, we solve for

$$P_1(\varepsilon) = \frac{2V + H(1+\varepsilon) + \varepsilon}{3}, \tag{8}$$

which is strictly below the upper bound of investor B's evaluation of $2V$.

With respect to the domain of ε, the equilibrium price $P_1(\varepsilon)$ falls into two cases,

$$\begin{aligned} \lim_{\varepsilon \to 1+\frac{2V^-}{H}} P_1(\varepsilon) &= \frac{4V+1}{3} + \frac{2}{3}\left(H + \frac{V}{H}\right), \\ \lim_{\varepsilon \to 1^+} P_1(\varepsilon) &= \frac{2(V+H)+1}{3}. \end{aligned} \tag{9}$$

Similarly, when $\varepsilon \to 1 + \frac{2V^-}{H}$, the equilibrium price is a U-shaped function of the heterogeneous belief H, and the lowest equilibrium price is achieved at $H = \sqrt{V}$.

At $t = 2$, we assume that S_B is revealed at time 1, and investor A engages in the auction process,

$$P_2(\varepsilon) = \frac{E_2\left(S_A\right) + E_2\left(S_B\right)}{2} = \frac{E_2\left(S_A \mid S_A \text{ is constrained }\right) + S_B}{2}. \tag{10}$$

Investor A's information is concealed only when she is bounded by short-selling restrictions. We assume that the cutoff value of A's belief is S_A^*. Then, $E_2\left(S_A \mid H\varepsilon \leq S_A \leq S_A^*\right)$ follows a uniform distribution of $[H\varepsilon, S_A^*]$, and thus $E_2\left(S_A \mid H\varepsilon \leq S_A \leq S_A^*\right) = \frac{S_A^* + H\varepsilon}{2}$. The auction price remains high until it goes to S_A^*. We solve for

$$P_2(\varepsilon) = \frac{H\varepsilon + 2S_B}{3}, \tag{11}$$

which strictly lies below the upper bound of investor A's evaluation of $H + 2V$.

Similarly, the equilibrium price also falls into two cases,

$$\begin{aligned} \lim_{\varepsilon \to 1+\frac{2V^-}{H}} P_2(\varepsilon) &= \frac{H+2V+2S_B}{3}, \\ \lim_{\varepsilon \to 1^+} P_2(\varepsilon) &= \frac{H+2S_B}{3}. \end{aligned} \tag{12}$$

In summary, based on Eqs. (5), (8), and (11), where the equilibrium prices increase with short-selling constraints ε, we argue that before the pilot program, the complete short-selling constraints in the Chinese equity market result in an equilibrium price that is higher than that observed in the benchmark model ($\varepsilon = 1$).

More importantly, we focus on market downturns characterized by the dominance of investors' pessimistic beliefs, which are likely to be concealed due to short-selling constraints. We summarize theoretical implications with respect to Eqs. (6), (9), and (12) in Proposition 1 and Proposition 2 as follows.

Proposition 1*: With short-selling constraints in China, the determination of equilibrium prices generally exhibit two scenarios: i) if the short-selling policy is stringent, i.e., $\varepsilon \to 1 + \frac{2V^-}{H}$, the equilibrium prices remain higher than the fundamental value; ii) if the short-selling policy is lenient, i.e., $\varepsilon \to 1^+$, the over-valuation of equilibrium prices reduces to a large extent.*

Proposition 2*: The equilibrium prices under stringent short-selling constraints in China largely depend on the degree of the heterogeneous belief:*

i) If the level of the heterogeneous belief is relatively large, the price would diverge more from the fundamental value;

ii) If the level of the heterogeneous belief is relatively low, which suggests that the trading behavior of institutional investors converges to the herding behavior of retail

investors in China, the equilibrium price remains divergent from the efficient price;

iii) If the level of the heterogeneous belief is at a reasonable cutoff, the equilibrium price converges to an efficient level. Therefore, mispricing is largely reduced.

Both propositions outline several possible outcomes for equilibrium prices depending on the adjustments of short-selling policies and the heterogeneous belief of market players in the market. Empirically, our results in Section 3 and Section 4 are largely consistent with both propositions. First, the stringent short-selling policy in China leads to equilibrium prices that exceed fundamental values, resulting in significant mispricing in the equity market. Second, when such stringent policies are paired with a moderate degree of heterogeneous beliefs between institutional and retail investors, mispricing is alleviated to a certain extent.

6. Conclusion

Short-selling in China is not banned but subject to stringent regulations and oversight. In this paper, we implement a comprehensive examination of the impact of short-selling on correcting mispricing in the Chinese equity market. Empirically, relying on 70 representative anomalies, we show that short-selling activities exhibit limited effects on mispricing correction for anomaly portfolio returns in China. The improved pricing efficiency only concentrates on stocks with a high short-selling ratio, yet considerable mispricing remains and cannot be systematically eliminated.

We also employ two exogenous shocks as natural experiments to confirm this finding. The first shock is an expansion of short-selling activities, known as the short-selling refinancing policy, and the second shock is a retraction that imposes a ban on "*t+0*" trading

rule. We further find that the effect of short selling on correcting mispricing is more pronounced in the trading-related anomalies than in the accounting-related anomalies.

We investigate the mechanisms of mispricing correction from the perspective of informed trading. When the level of informed trading is higher, we find that in the designated stocks, the difference in anomaly returns between the high and low short-selling ratio groups is more pronounced. However, too extreme informed trading undermines price discovery of short-selling activities. In addition, we find that institutional investors, who are often considered as informed traders and short sellers, can accurately detect the anomaly-implied trading directions, in particular, in the trading-related anomalies rather than the accounting-related anomalies. Our subsample tests reveal that mispricing correction concentrates on stocks characterized by weak corporate governance and poor information environments.

Our study offers novel insights into the real effects of China's short-selling reform. Due to the stringency of the regulatory frameworks and the predominance of retail investors, the price discovery function of China's short-selling mechanism remains inefficient.

References

Allen, F., J. Qian, C. Shan, and J. L. Zhu (2024). Dissecting the long-term performance of the Chinese stock market. *The Journal of Finance 79*(2), 993–1054.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Amihud, Y., H. Mendelson, and B. Lauterbach (1997). Market microstructure and securities values: Evidence from the tel aviv stock exchange. *Journal of Financial Economics 45*(3), 365–390.

Bharath, S. T., P. Pasquariello, and G. Wu (2009). Does asymmetric information drive capital structure decisions? *The Review of Financial Studies 22*(8), 3211–3243.

Birru, J., S. Gokkaya, X. Liu, and S. Markov (2024). Quants and market anomalies. *Journal of Accounting and Economics*, 101688.

Blau, B. M. and J. M. Pinegar (2013). Are short sellers incrementally informed prior to earnings announcements? *Journal of Empirical Finance 21*, 142–155.

Boehmer, E., C. M. Jones, J. Wu, and X. Zhang (2020). What do short sellers know? *Review of Finance 24*(6), 1203–1235.

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

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

Boehmer, E. and J. Wu (2013). Short selling and the price discovery process. *The Review of Financial Studies 26*(2), 287–322.

Bradshaw, M., G. Liao, and M. S. Ma (2019). Agency costs and tax planning when the government is a major shareholder. *Journal of Accounting and Economics 67*(2-3), 255–277.

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

Brockman, P. and D. Y. Chung (2000). An empirical investigation of trading on asymmetric information and heterogeneous prior beliefs. *Journal of Empirical Finance 7*(5), 417–454.

Callen, J. L. and X. Fang (2015). Short interest and stock price crash risk. *Journal of Banking & Finance 60*, 181–194.

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

Chang, E. C., Y. Luo, and J. Ren (2014). Short-selling, margin-trading, and price efficiency: Evidence from the Chinese market. *Journal of Banking & Finance 48*, 411–424.

Chen, H., M. Gu, and B. Ni (2023). How price limit affects the market efficiency in a short-sale constrained market? evidence from a quasi-natural experiment. *Journal of Empirical Finance 73*, 22–39.

Chen, X. and C. Wu (2022). Retail investor attention and information asymmetry: Evidence from China. *Pacific-Basin Finance Journal 75*, 101847.

Chi, Y., J. He, F. Wu, and B. Yin (2022). Optimal information production of mutual funds: evidence from China. *Journal of Banking & Finance 143*, 106585.

Christophe, S. E., M. G. Ferri, and J. Hsieh (2010). Informed trading before analyst downgrades: Evidence from short sellers. *Journal of Financial Economics 95*(1), 85–106.

Chu, Y., D. Hirshleifer, and L. Ma (2020). The causal effect of limits to arbitrage on asset pricing anomalies. *The Journal of Finance 75*(5), 2631–2672.

Deng, X., L. Gao, and J.-B. Kim (2020). Short-sale constraints and stock price crash risk: Causal evidence from a natural experiment. *Journal of Corporate Finance 60*, 101498.

Diamond, D. W. (1985). Optimal release of information by firms. *The Journal of Finance 40*(4), 1071–1094.

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

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

Easley, D., M. M. L. De Prado, and M. O'Hara (2011). The microstructure of the" flash crash": Flow toxicity, liquidity crashes, and the probability of informed trading. *Journal of Portfolio Management 37*(2), 118.

Easley, D., S. Hvidkjaer, and M. O'hara (2002). Is information risk a determinant of asset returns? *The Journal of Finance 57*(5), 2185–2221.

Easley, D., M. M. López de Prado, and M. O'Hara (2012). Flow toxicity and liquidity in a high-frequency world. *The Review of Financial Studies 25*(5), 1457–1493.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy 81*(3), 607–636.

Gao, X. and Y. Wang (2023). Mining the short side: Institutional investors and stock market anomalies. *Journal of Financial and Quantitative Analysis 58*(1), 392–418.

Green, J., J. R. Hand, and X. F. Zhang (2017). The characteristics that provide independent information about average us monthly stock returns. *The Review of Financial Studies 30*(12), 4389–4436.

Harrison, J. M. and D. M. Kreps (1978). Speculative investor behavior in a stock market with heterogeneous expectations. *The Quarterly Journal of Economics 92*(2), 323–336.

Ho, K.-C., L. Yang, and S. Luo (2022). Information disclosure ratings and continuing overreaction: Evidence from the Chinese capital market. *Journal of Business Research 140*, 638–656.

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

Hou, K., F. Qiao, and X. Zhang (2023). Finding anomalies in China. *Fisher College of Business Working Paper* (2023-03), 002.

Huang, A. G., H. Tan, and R. Wermers (2020). Institutional trading around corporate news: Evidence from textual analysis. *The Review of Financial Studies 33*(10), 4627–4675.

Jiang, C. and X. Wang (2024). Portfolio pumping and dumping among Chinese mutual fund companies. *Journal of Banking & Finance 162*, 107155.

Jiang, F. and K. A. Kim (2015). Corporate governance in China: A modern perspective. *Journal of Corporate Finance 32*, 190–216.

Jiang, H., A. Habib, and M. M. Hasan (2022). Short selling: A review of the literature and implications for future research. *European Accounting Review 31*(1), 1–31.

Kanagaretnam, K., G. J. Lobo, and D. J. Whalen (2007). Does good corporate governance reduce information asymmetry around quarterly earnings announcements? *Journal of Accounting and Public policy 26*(4), 497–522.

Leippold, M., Q. Wang, and W. Zhou (2022). Machine learning in the Chinese stock market. *Journal of Financial Economics 145*(2), 64–82.

Li, W., G. Rhee, and S. S. Wang (2017). Differences in herding: Individual vs. institutional investors. *Pacific-Basin Finance Journal 45*, 174–185.

Li, W. and S. S. Wang (2010). Daily institutional trades and stock price volatility in a retail investor dominated emerging market. *Journal of Financial Markets 13*(4), 448–474.

Li, Z., L. X. Liu, X. Liu, and K. J. Wei (2024). Replicating and digesting anomalies in the Chinese a-share market. *Management Science 70*(8), 5066–5090.

Liu, J., R. F. Stambaugh, and Y. Yuan (2019). Size and value in China. *Journal of Financial Economics 134*(1), 48–69.

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

Muravyev, D., N. D. Pearson, and J. M. Pollet (2025). Anomalies and their short-sale costs. *Available at SSRN 4266059*.

Nagel, S. (2005). Short sales, institutional investors and the cross-section of stock returns. *Journal of Financial Economics 78*(2), 277–309.

Newey, W. K. and K. D. West (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 777–787.

Ni, X. and S. Yin (2020). The unintended real effects of short selling in an emerging market. *Journal of Corporate Finance 64*, 101659.

Pástor, L. and R. F. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political Economy 111*(3), 642–685.

Qiao, F. (2024). Do analysts disseminate anomaly information in China? *Journal of Banking & Finance 165*, 107221.

Tan, L., X. Zhang, and X. Zhang (2023). Retail and institutional investor trading behaviors: evidence from China. *Annual Review of Financial Economics 16*.

Titman, S., C. Wei, and B. Zhao (2022). Corporate actions and the manipulation of retail investors in China: An analysis of stock splits. *Journal of Financial Economics 145*(3), 762–787.

Verrecchia, R. E. (1982). Information acquisition in a noisy rational expectations economy. *Econometrica: Journal of the Econometric Society*, 1415–1430.

Wan, X. (2020). The impact of short-selling and margin-buying on liquidity: Evidence from the Chinese stock market. *Journal of Empirical Finance 55*, 104–118.

Wang, F. A. (1998). Strategic trading, asymmetric information and heterogeneous prior beliefs. *Journal of Financial Markets 1*(3-4), 321–352.

Wang, S., H. Yan, N. Zhong, and Y. Tang (2024). Indirect effects of trading restrictions. *Journal of Corporate Finance 86*, 102580.

Table 1: Timeline of revisions for the list of the eligible stocks

The table reports the timeline of major revisions of short-selling and margin-buying regulation in the Chinese stock market. The regulatory agency first releases the list of designated stocks on *Announcement Date*, and the designated stocks are allowed to be bought on margin or shorted on the *Effective Date*. *No. added* refers to the number of stocks newly added to the list on/between the announcement dates. *No. removed* refers to the number of stocks removed from the list on/between the announcement dates. *No. on the list* refers to the number of stocks remaining on the list on/between the announcement dates.

Announcement Date (Effective Date)	No. added	No. removed	No. on the list
2010/02/12 (2010/03/31)	90	0	90
From 2010/04/01 to 2011/12/04	6	6	90
2011/11/25 (2011/12/05)	189	1	278
From 2011/12/06 to 2013/01/30	0	0	278
2013/01/25 (2013/01/31)	276	54	500
From 2013/02/01 to 2013/09/15	0	6	494
2013/09/06 (2013/09/16)	206	0	700
From 2013/09/17 to 2014/09/21	0	5	695
2014/09/12 (2014/09/22)	218	13	900
From 2014/09/23 to 2016/12/11	0	27	873
2016/12/02 (2016/12/12)	77	0	950
From 2016/12/13 to 2019/08/18	81	81	950
2019/08/09 (2019/08/19)	650	0	1600
From 2019/08/20 to 2022/06/30	95	95	1600

Table 2: Summary statistics of treated and control Stocks and representative anomalies

Panel A reports the PSM comparison results across three matching variables of size, turnover rate, and trading amount. The mean of the natural logarithm of market capitalization, turnover rate, and trading amount for untreated, treated, and control stocks, as well as the mean differences and t-value in parentheses are reported. Panel B reports summary statistics for long-short anomaly returns in each of six categories across control stocks, treated stocks, and the combination of both. The monthly average returns, standard deviations, 25th percentiles, medians, and 75th percentiles are all reported in percent. The sample period spans from March 2010 to June 2022. ***/**/* indicate the significance at the 1%, 5% and 10% confidence level, respectively.

Panel A: Treated and Control Stocks

	N	Size	Turnover	Trading amount		**N**	Size	Turnover	Trading amount
Treated	161,585	22.118	3.527	21.053	Treated	93,548	22.163	3.562	21.133
Untreated	120,779	23.366	3.193	21.966	Control	93,548	22.988	3.292	21.688
Diff		−1.249***	0.334***	−0.912***	Diff		−0.824***	0.270***	−0.554***

Panel B: Representative Anomalies

Category	N	Mean	Std. Dev.	P25	Median	P75
Panel B.1: Control stocks						
Investment	148	0.307	1.143	-0.364	0.258	0.910
Past return	148	0.748	2.403	-0.768	0.523	2.081
Profitability	148	0.481	1.598	-0.537	0.500	1.328
Risk	148	0.193	4.962	-3.699	0.495	3.136
Trading friction	148	0.819	3.559	-1.498	0.908	3.023
Value	148	0.982	2.835	-0.842	0.859	2.745
Panel B.2: Treated stocks						
Investment	148	0.073	1.090	-0.497	0.093	0.596
Past return	148	0.508	2.349	-1.144	0.492	1.989
Profitability	148	0.335	1.287	-0.410	0.360	1.082
Risk	148	0.355	4.853	-2.894	1.245	3.798
Trading friction	148	0.697	3.020	-1.144	1.013	2.577
Value	148	0.677	2.649	-1.133	0.622	2.254
Panel B.3: Control & Treated stocks						
Investment	148	0.331	1.193	-0.424	0.347	1.073
Past return	148	0.659	2.247	-0.930	0.455	2.030
Profitability	148	0.403	1.247	-0.427	0.393	1.250
Risk	148	0.404	4.996	-3.290	0.938	3.959
Trading friction	148	0.749	3.076	-1.118	0.969	2.888
Value	148	0.770	2.476	-0.867	0.672	2.463

Table 3: Summary statistics of 70 characteristic-managed portfolios

Panel A, B and C report the raw excess returns, CAPM adjusted alphas, and Liu et al. (2019) four factor-adjusted alphas of the long-short portfolios, long-leg portfolios, and short-leg portfolios across six categories, respectively. For each category, we calculate the equal-weighted average returns with the corresponding t-statistics reported in parentheses. Sample period spans from March 2010 to June 2022. Standard errors are adjusted with Newey and West (1987) five lag correction. ***/**/* indicate the significance at the 1%, 5% and 10% confidence level, respectively.

	Raw returns (%)			**CAPM alpha (%)**			**LSY-4 alpha (%)**		
	Control	**Treated**	**Difference**	**Control**	**Treated**	**Difference**	**Control**	**Treat**	**Difference**
Panel A: Long-short Portfolios									
Investment	0.307***	0.073	**-0.234***	0.306***	0.068	**-0.238***	0.375***	0.146*	**-0.229***
	(3.074)	(1.008)	**(-1.713)**	(3.174)	(0.910)	**(-1.787)**	(4.090)	(1.872)	**(-1.744)**
Past return	0.748***	0.508***	**-0.241**	0.764***	0.529***	**-0.234**	0.997***	0.755***	**-0.242**
	(3.940)	(2.935)	**(-1.277)**	(4.199)	(3.063)	**(-1.252)**	(4.833)	(3.932)	**(-1.229)**
Profitability	0.481***	0.335***	**-0.145**	0.484***	0.350***	**-0.135**	0.628***	0.440***	**-0.188**
	(3.500)	(3.096)	**(-1.194)**	(3.610)	(3.175)	**(-1.076)**	(4.389)	(4.116)	**(-1.420)**
Risk	0.193	0.355	0.163	0.294	0.473	0.179	-0.436	-0.331	0.105
	(0.584)	(1.086)	(0.808)	(0.892)	(1.577)	(0.851)	(-1.446)	(-1.283)	(0.479)
Trading friction	0.819***	0.697***	**-0.122**	0.883***	0.765***	**-0.118**	0.331	0.234	**-0.097**
	(3.364)	(3.513)	**(-0.636)**	(3.629)	(4.054)	**(-0.606)**	(1.337)	(1.379)	**(-0.474)**
Value	0.982***	0.677***	**-0.305**	0.991***	0.719***	**-0.272**	1.315***	0.775***	**-0.540*** **
	(3.752)	(3.152)	**(-1.654)**	(3.912)	(3.321)	**(-1.338)**	(5.079)	(3.370)	**(-2.686)**
Panel B: Long-leg Portfolios									
Investment	0.73	0.718	**-0.012**	0.385	0.377**	**-0.008**	0.534***	0.321**	**-0.213**
	(1.152)	(1.260)	**(-0.051)**	(1.259)	(2.047)	**(-0.034)**	(3.602)	(2.249)	**(-1.260)**
Past return	1.053	0.76	**-0.293**	0.707**	0.431*	**-0.276**	0.949***	0.529**	**-0.420****
	(1.626)	(1.311)	**(-1.262)**	(2.047)	(1.790)	**(-1.221)**	(4.409)	(2.581)	**(-2.277)**
Profitability	0.849	0.754	**-0.094**	0.508*	0.429**	**-0.079**	0.645***	0.347**	**-0.298***
	(1.399)	(1.377)	**(-0.441)**	(1.661)	(2.419)	**(-0.368)**	(4.125)	(2.349)	**(-1.906)**
Risk	0.591	0.721	0.131	0.302	0.460***	0.159	0.051	0.003	**-0.048**
	(1.024)	(1.532)	(0.497)	(1.154)	(2.989)	(0.626)	(0.308)	(0.026)	**(-0.267)**
Trading friction	0.748	0.824	0.076	0.444*	0.531***	0.087	0.272*	0.207*	**-0.065**
	(1.331)	(1.643)	(0.348)	(1.751)	(3.436)	(0.401)	(1.915)	(1.770)	**(-0.408)**
Value	1.142*	0.966*	**-0.177**	0.809***	0.659***	**-0.15**	1.012***	0.523***	**-0.489*** **
	(1.912)	(1.796)	**(-0.782)**	(2.738)	(3.936)	**(-0.667)**	(4.483)	(3.064)	**(-2.860)**
Panel C: Short-leg Portfolios									
Investment	0.423	0.645	0.222	0.079	0.309	0.231	0.159	0.175	0.016
	(0.690)	(1.147)	(1.092)	(0.273)	(1.633)	(1.122)	(1.304)	(1.235)	(0.106)
Past return	0.304	0.252	**-0.052**	-0.057	-0.098	**-0.041**	-0.048	-0.225	**-0.177**
	(0.468)	(0.418)	**(-0.246)**	(-0.181)	(-0.423)	**(-0.197)**	(-0.326)	(-1.001)	**(-1.044)**
Profitability	0.367	0.419	0.052	0.023	0.08	0.057	0.016	-0.093	**-0.109**
	(0.579)	(0.745)	(0.230)	(0.077)	(0.454)	(0.262)	(0.111)	(-0.662)	**(-0.614)**
Risk	0.398	0.366	**-0.032**	0.008	-0.013	**-0.021**	0.487*	0.334	**-0.153**
	(0.537)	(0.563)	**(-0.129)**	(0.019)	(-0.045)	**(-0.085)**	(1.892)	(1.327)	**(-0.695)**
Trading friction	-0.071	0.127	0.198	-0.439	-0.234	0.205	-0.059	-0.027	0.032
	(-0.104)	(0.210)	(0.814)	(-1.202)	(-1.026)	(0.864)	(-0.266)	(-0.133)	(0.159)
Value	0.161	0.289	0.129	-0.182	-0.061	0.121	-0.303*	-0.252	0.05
	(0.246)	(0.498)	(0.620)	(-0.586)	(-0.280)	(0.586)	(-1.717)	(-1.335)	(0.259)

Table 4: DiD regressions

This table reports the DiD regression result. The dependent variables are the returns of long-short representative anomalies in Panel A, while in Panel B and C are excess returns of long-leg and short-leg representative anomalies. The dummy variable equals one if the portfolios are constructed from treated stocks, and zero otherwise. Sample period spans from March 2010 to June 2022. Year fixed effect and control variables of Liu et al. (2019) factor returns are included. The corresponding t-statistics reported in parentheses. ***/**/* indicate the significance at the 1%, 5% and 10% confidence level, respectively.

	(1) Investment	(2) Past return	(3) Profitability	(4) Risk	(5) Trading friction	(6) Value
Panel A: Long-Short Portfolios						
TREAT* × *POST	-0.234*	-0.241	-0.145	0.163	-0.122	-0.305
	(-1.833)	(-0.926)	(-0.894)	(0.429)	(-0.439)	(-1.062)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	296	296	296	296	296	296
Adjusted R-squared	0.042	0.115	0.073	0.557	0.474	0.188
Panel B: Long-leg Portfolios						
TREAT* × *POST	-0.012	-0.293	-0.094	0.131	0.076	-0.177
	(-0.052)	(-1.091)	(-0.412)	(0.515)	(0.342)	(-0.673)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	296	296	296	296	296	296
Adjusted R-squared	0.937	0.912	0.930	0.877	0.918	0.898
Panel C: Short-leg Portfolios						
TREAT* × *POST	0.222	-0.052	0.052	-0.032	0.198	0.129
	(0.954)	(-0.188)	(0.220)	(-0.093)	(0.694)	(0.463)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	296	296	296	296	296	296
Adjusted R-squared	0.930	0.912	0.929	0.893	0.914	0.905

Table 5: Patterns of anomaly returns across groups of short-selling ratio

This table reports number of portfolios with positive returns, portfolios with significantly positive returns (at the 10% level), and pooled average returns in treated stocks with different levels of short-selling ratio. Panel A, B and C report the raw excess returns, CAPM adjusted alphas, and Liu et al. (2019) four factor-adjusted alphas of the long-short portfolios, long-leg portfolios, and short-leg portfolios across six categories, respectively. Sample period spans from March 2010 to June 2022. Standard errors are adjusted with Newey and West (1987) five lag correction.

	Raw excess return		**CAPM alpha**		**LSY-4 alpha**	
N	**Return > 0 [Signif.]**	**Avg return (%)**	**Return > 0 [Signif.]**	**Avg return (%)**	**Return > 0 [Signif.]**	**Avg return (%)**
Panel A: Long-short Portfolios						
Low shorting ratio	56 [15]	0.386	54 [23]	0.454	46 [22]	0.367
Medium shorting ratio	56 [15]	0.413	57 [21]	0.491	53 [26]	0.448
High shorting ratio	**49 [10]**	**0.31**	**52 [15]**	**0.37**	**38 [18]**	**0.242**
Panel B: Long-leg Portfolios						
Low shorting ratio	70 [50]	1.208	67 [31]	0.559	51 [22]	0.306
Medium shorting ratio	70 [33]	0.992	59 [21]	0.358	41 [8]	0.064
High shorting ratio	**65 [3]**	**0.497**	**24 [3]**	**-0.177**	**27 [6]**	**-0.155**
Panel C: Short-leg Portfolios						
Low shorting ratio	70 [18]	0.822	41 [7]	0.105	32 [3]	-0.061
Medium shorting ratio	68 [1]	0.579	26 [1]	-0.133	8 [0]	-0.384
High shorting ratio	**47 [1]**	**0.191**	**6 [0]**	**-0.545**	**10 [1]**	**-0.399**

Table 6: Two natural experiments

The table implements two natural experiments. Panel A investigates the short-selling refinancing policy from September 2013 to May 2015. Panel B investigates the shock of ban on "t+0" trading rule from August 2015 to April 2016. Reported results are monthly raw excess returns, CAPM-adjusted alphas, and LSY-4 factor adjusted alphas of representative anomalies in percent. Standard errors are adjusted with Newey and West (1987) five lag correction. ***/**/* indicate the significance at the 1%, 5% and 10% confidence level, respectively.

Panel A: The Short-Selling Refinancing Policy

	Raw returns (%)			**CAPM alpha (%)**			**LSY-4 alpha (%)**		
	Control	**Treated**	**Difference**	**Control**	**Treated**	**Difference**	**Control**	**Treated**	**Difference**
Investment	0.118	-0.227**	**-0.345**	-0.070	-0.184*	**-0.114**	-0.152	-0.205	**-0.053**
	(0.743)	(-2.252)	**(-1.596)**	(-0.479)	(-1.984)	**(-0.660)**	(-1.335)	(-1.130)	**(-0.301)**
Past return	0.531	0.224	**-0.308**	0.694*	0.562	**-0.132**	0.682*	0.679	**-0.003**
	(1.412)	(0.548)	**(-1.055)**	(1.801)	(1.689)	**(-0.577)**	(1.981)	(1.329)	**(-0.009)**
Profitability	0.125	-0.086	**-0.211**	0.154	0.139	**-0.015**	0.117	-0.010	**-0.127**
	(0.564)	(-0.568)	**(-1.448)**	(0.673)	(0.848)	**(-0.085)**	(0.399)	(-0.073)	**(-0.527)**
Risk	0.561	0.097	**-0.464**	1.019	0.293	**-0.726****	0.515	-0.470	**-0.985****
	(1.016)	(0.220)	**(-1.466)**	(1.550)	(0.421)	**(-2.315)**	(1.485)	(-0.952)	**(-2.488)**
Trading friction	0.703***	0.225	**-0.478****	0.933***	0.306	**-0.626****	0.054	-0.440	**-0.494**
	(3.070)	(0.931)	**(-2.450)**	(3.363)	(0.990)	**(-2.498)**	(0.171)	(-1.487)	**(-1.233)**
Value	-0.085	-0.232	**-0.147**	0.000	-0.188	**-0.188**	0.033	-0.376	**-0.408**
	(-0.232)	(-0.566)	**(-0.607)**	0.000	(-0.458)	**(-0.539)**	(0.059)	(-0.792)	**(-1.291)**

Panel B: The Ban on "t+0" Trading Rule

	Raw returns (%)			**CAPM alpha (%)**			**LSY-4 alpha (%)**		
	Control	**Treated**	**Difference**	**Control**	**Treated**	**Difference**	**Control**	**Treated**	**Difference**
Investment	-0.037	0.120	**0.157**	-0.025	0.126	**0.151**	0.062	0.460	**0.398**
	(-0.205)	(1.236)	**(1.313)**	(-0.138)	(1.321)	**(1.155)**	(0.288)	(1.960)	**(1.007)**
Past return	0.575**	-0.151	-0.726	0.562**	-0.198	-0.760	-0.068	1.027	**1.095**
	(2.555)	(-0.220)	(-1.310)	(2.618)	(-0.301)	(-1.456)	(-0.162)	(0.910)	**(0.690)**
Profitability	0.426*	0.367***	-0.059	0.421*	0.369***	-0.052	-0.174	0.052	**0.227**
	(2.133)	(3.582)	(-0.340)	(2.043)	(3.659)	(-0.309)	(-0.593)	(0.096)	**(0.516)**
Risk	-1.386	-0.492	**0.895****	-1.199*	-0.254	**0.945*****	-0.707	-0.507	**0.2**
	(-1.407)	(-0.409)	**(3.223)**	(-1.990)	(-0.397)	**(4.935)**	(-1.602)	(-1.374)	**(0.584)**
Trading friction	-0.013	0.034	**0.047**	0.12	0.191	**0.072**	-0.003	-1.290*	-1.287
	(-0.025)	(0.043)	**(0.142)**	(0.542)	(0.600)	**(0.246)**	(-0.004)	(-2.720)	(-2.129)
Value	0.768***	0.247	-0.521*	0.811***	0.297	-0.513	-0.779*	-0.495	**0.284**
	(3.512)	(0.942)	(-1.912)	(4.385)	(1.403)	(-1.875)	(-2.512)	(-1.453)	**(0.452)**

Table 7: Analysis on short-selling ratio and informed trading

This table reports 3*5 double-sorted portfolios on short-selling ratio and informed trading in treated stocks. HML (VPIN) refer to high-VPIN ("5") minus low-VPIN ("1") portfolio returns conditional on each group of short-selling ratio. LMH (SSR) refer to low-SSR ("1") minus high-SSR ("3") portfolio returns conditional on each group of VPIN. Ucon. (VPIN) refers to single-sorted quintile portfolio returns based on VPIN and extreme quintile portfolio return differences. Ucon. (SSR) refers to single-sorted portfolio returns based on short-selling ratio and extreme portfolio return differences. Sample period spans from March 2010 to June 2022. Panel A and B report raw excess returns and CAPM-adjusted alphas with the corresponding t-statistics reported in parentheses. Standard errors are adjusted with Newey and West (1987) five lag correction. ***/**/* indicate the significant returns at the 1%, 5% and 10% confidence level, respectively.

Panel A: Raw excess return

Short-selling ratio	VPIN						
	1	2	3	4	5	HML (VPIN)	Ucon. (SSR)
1	0.810	1.140*	0.88	1.395**	1.270*	0.460	1.138*
	(1.322)	(1.852)	(1.470)	(2.043)	(1.920)	(1.035)	(1.916)
2	0.720	0.806	0.875	0.952	0.992	0.272	0.870
	(1.135)	(1.331)	(1.461)	(1.427)	(1.590)	(0.757)	(1.440)
3	0.114	0.322	0.052	0.491	0.957	**0.842****	0.384
	(0.180)	(0.480)	(0.080)	(0.705)	(1.468)	**(2.165)**	(0.622)
LMH (SSR)	**0.696***	**0.818*****	**0.828****	**0.904*****	**0.313**		**0.754*****
	(1.942)	**(2.703)**	**(2.489)**	**(2.726)**	**(0.812)**		**(3.443)**
Ucon. (VPIN)	0.636	0.702	0.585	0.780	1.134*	0.498	
	(1.099)	(1.116)	(0.992)	(1.198)	(1.825)	(1.339)	

Panel B: CAPM alpha

Short-selling ratio	VPIN						
	1	2	3	4	5	HML (VPIN)	Ucon. (SSR)
1	0.174	0.461	0.178	0.685**	0.604	0.430	0.467*
	(0.553)	(1.654)	(0.674)	(2.088)	(1.410)	(0.922)	(1.859)
2	0.069	0.159	0.243	0.245	0.311	0.243	0.210
	(0.290)	(0.646)	(0.920)	(0.792)	(1.068)	(0.665)	(1.008)
3	-0.580**	-0.379	-0.646**	-0.289	0.256	**0.835****	-0.327
	(-2.009)	(-1.372)	(-2.058)	(-0.953)	(0.891)	**(2.147)**	(-1.599)
LMH (SSR)	**0.753****	**0.840*****	**0.824****	**0.974*****	**0.348**		**0.794*****
	(2.150)	**(2.791)**	**(2.481)**	**(2.854)**	**(0.928)**		**(3.695)**
Ucon. (VPIN)	0.002	0.001	0.093	0.055	0.424	0.422	
	(0.009)	(0.004)	(-0.377)	(0.231)	(1.465)	(1.105)	

Table 8: Anomaly-implied trading directions and institutional ownership

This table reports regression results of institutional ownership on trading directions implied by anomalies. Control variables include the natural logarithm of market capitalization, the natural logarithm of the book-to-market ratio, CAPM beta, illiquidity of Amihud (2002) ratio, past 1-month cumulative return, past 11-month cumulative return (skipping the most recent month), and return volatility. All continuous variables are winsorized at 1% and 99%. Sample period spans from March 2010 to June 2022. ***/**/* indicate the significant returns at the 1%, 5% and 10% confidence level, respectively.

	(1) **IO**	**(2)** **IO**	**(3)** **IO**	**(4)** **IO**	**(5)** **IO**	**(6)** **IO**	**(7)** **IO**
Short-selling ratio	**-6.266*** **	-6.572***	-4.484***	-5.423***	0.978	2.07	-3.379*
	(-7.307)	(-4.748)	(-3.126)	(-3.679)	(0.567)	(1.539)	(-1.805)
$\text{Trade}_{\text{Investment}}$		-0.000					
		(-0.070)					
SSR*$\text{Trade}_{\text{Investment}}$		0.151					
		(0.198)					
$\text{Trade}_{\text{Past return}}$			**0.004*** **				
			(2.906)				
SSR*$\text{Trade}_{\text{Past return}}$			-0.897				
			(-1.366)				
$\text{Trade}_{\text{Profitability}}$				0.000			
				(0.011)			
SSR*$\text{Trade}_{\text{Profitability}}$				-0.424			
				(-0.608)			
$\text{Trade}_{\text{Risk}}$					**0.004** **		
					(2.314)		
SSR*$\text{Trade}_{\text{Risk}}$					**-3.893*** **		
					(-4.696)		
$\text{Trade}_{\text{Trading friction}}$						**0.020*** **	
						(11.912)	
SSR*$\text{Trade}_{\text{Trading friction}}$						**-4.514*** **	
						(-5.188)	
$\text{Trade}_{\text{Value}}$							-0.001
							(-0.684)
SSR*$\text{Trade}_{\text{Value}}$							**-1.452***
							(-1.647)
Constant	-0.384***	-0.384***	-0.391***	-0.386***	-0.389***	-0.455***	-0.393***
	(-2.601)	(-2.596)	(-2.646)	(-2.614)	(-2.635)	(-3.096)	(-2.658)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	84,221	84,221	84,221	84,221	84,221	84,221	84,221
Adjusted R-squared	0.849	0.849	0.849	0.849	0.849	0.849	0.849

Table 9: Asymmetric anomaly-implied trading directions and institutional ownership

This table reports regression results of institutional ownership on asymmetric trading directions implied by anomalies. Control variables include the log of market capitalization, the log of the book-to-market ratio, CAPM beta, illiquidity of Amihud (2002) ratio, past 1-month cumulative return, past 11-month cumulative return (skipping the most recent month), and return volatility. All continuous variables are winsorized at 1% and 99%. Sample period spans from March 2010 to June 2022. ***/**/* indicate the significant returns at the 1%, 5% and 10% confidence level, respectively.

	(1) IO	(2) IO	(3) IO	(4) IO	(5) IO	(6) IO	(7) IO
Short-selling ratio	**-6.266*** (-7.307)**	-6.312*** (-7.447)	-6.134*** (-7.166)	-6.233*** (-7.042)	-6.311*** (-7.165)	-6.598*** (-7.205)	-6.082*** (-6.870)
$\text{Trade}_{\text{Investment}^+}$		-0.002 (-0.794)					
$\text{SSR*Trade}_{\text{Investment}^+}$		1.613 (1.159)					
$\text{Trade}_{\text{Investment}^-}$		0.002 (0.760)					
$\text{SSR*Trade}_{\text{Investment}^-}$		-2.698 (-1.276)					
$\text{Trade}_{\text{Past return}^+}$			**0.003*** (1.815)**				
$\text{SSR*Trade}_{\text{Past return}^+}$			**-1.975* (-1.936)**				
$\text{Trade}_{\text{Past return}^-}$			**-0.004* (-1.922)**				
$\text{SSR*Trade}_{\text{Past return}^-}$			-0.625 (-0.388)				
$\text{Trade}_{\text{Profitability}^+}$				-0.001 (-0.411)			
$\text{SSR*Trade}_{\text{Profitability}^+}$				-0.033 (-0.021)			
$\text{Trade}_{\text{Profitability}^-}$				0.001 (0.271)			
$\text{SSR*Trade}_{\text{Profitability}^-}$				-1.118 (-0.554)			
$\text{Trade}_{\text{Risk}^+}$					**0.009*** (3.012)**		
$\text{SSR*Trade}_{\text{Risk}^+}$					**-16.336*** (-3.676)**		
$\text{Trade}_{\text{Risk}^-}$					**-0.003 (-1.265)**		
$\text{SSR*Trade}_{\text{Risk}^-}$					**3.090** (2.250)**		
$\text{Trade}_{\text{Trading friction}^+}$						**0.022*** (8.684)**	
$\text{SSR*Trade}_{\text{Trading friction}^+}$						**-19.744*** (-4.159)**	
$\text{Trade}_{\text{Trading friction}^-}$						**-0.028*** (-10.907)**	
$\text{SSR*Trade}_{\text{Trading friction}^-}$						**6.827*** (4.875)**	
$\text{Trade}_{\text{Value}^+}$							-0.000 (-0.077)
$\text{SSR*Trade}_{\text{Value}^+}$							**-3.779* (-1.843)**
$\text{Trade}_{\text{Value}^-}$							0.003 (1.034)
$\text{SSR*Trade}_{\text{Value}^-}$							-1.449 (-0.658)
Constant	-0.384*** (-2.601)	-0.386*** (-2.608)	-0.386*** (-2.609)	-0.385*** (-2.608)	-0.386*** (-2.614)	-0.430*** (-2.936)	-0.398*** (-2.690)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	84,221	84,221	84,221	84,221	84,221	84,221	84,221
Adjusted R-squared	0.849	0.849	0.849	0.849	0.849	0.849	0.849

Table 10: Analysis on short-selling ratio and asymmetric information

This table reports the 3*5 double-sorted portfolios on short-selling ratio and information asymmetry in treated stocks. LMH (Asy) refers to low-Asy ("1") minus high-Asy ("5") portfolio returns within each group of short-selling ratio. LMH (SSR) refer to low-SSR ("1") minus high-SSR ("3") portfolio returns within each group of information asymmetry. Ucon. (Asy) refers to single-sorted quintile portfolio returns on information asymmetry and extreme quintile portfolio return differences. Ucon. (SSR) refers to single-sorted portfolio returns based on short-selling ratio and extreme portfolio return differences. Sample period spans from March 2010 to June 2022. Panel A and B report raw excess returns and CAPM-adjusted alphas with the corresponding t-statistics reported in parentheses. Standard errors are adjusted with Newey and West (1987) five lag correction. ***/**/* indicate the significant returns at the 1%, 5% and 10% confidence level, respectively.

Panel A: Raw excess return

Short-selling ratio	Information asymmetry						
	1	2	3	4	5	LMH (Asy)	Ucon. (SSR)
1	2.196***	0.958	1.006	0.349	0.137	**2.059*** **	1.138*
	(3.270)	(1.480)	(1.560)	(0.550)	(0.220)	**(3.900)**	(1.920)
2	1.975***	0.853	0.348	0.014	-0.276	**2.251*** **	0.870
	(2.740)	(1.390)	(0.550)	(0.020)	(-0.442)	**(4.320)**	(1.440)
3	1.431**	0.55	-0.148	-0.21	-0.951	**2.381*** **	0.384
	(2.100)	(0.800)	(-0.219)	(-0.340)	(-1.392)	**(5.060)**	(0.620)
LMH (SSR)	0.765**	0.408	1.154***	0.559	1.087***		**0.754*** **
	(2.212)	(1.365)	(3.457)	(1.643)	(3.663)		**(3.443)**
Ucon. (Asy)	1.542**	0.687	0.404	0.202	-0.152	1.694***	
	(2.401)	(1.105)	(0.670)	(0.330)	(-0.246)	(4.127)	

Panel B: CAPM alpha

Short-selling ratio	Information asymmetry						
	1	2	3	4	5	LMH (Asy)	Ucon. (SSR)
1	1.533***	0.260	0.309	-0.322	-0.544*	**2.076*** **	0.467*
	(3.424)	(0.985)	(1.022)	(-0.988)	(-1.800)	**(3.922)**	(1.859)
2	1.309***	0.195	-0.328	-0.660***	-0.948***	**2.257*** **	0.210
	(3.041)	(0.743)	(-1.342)	(-2.832)	(-4.030)	**(4.326)**	(1.008)
3	0.714*	-0.184	-0.888***	-0.898***	-1.665***	**2.378*** **	-0.327
	(1.885)	(-0.671)	(-4.070)	(-3.532)	(-5.201)	**(5.153)**	(-1.599)
LMH (SSR)	0.819**	0.444	1.196***	0.575	1.121***		**0.794*** **
	(2.327)	(1.499)	(3.971)	(1.657)	(3.914)		**(3.695)**
Ucon. (Asy)	0.863***	-0.012	-0.28	-0.504**	-0.841***	1.704***	
	(2.832)	(-0.062)	(-1.278)	(-2.399)	(-3.430)	(4.216)	

Table 11: Subsample tests

This table reports subsample results of raw excess returns of long-short anomalies. The three set of subsamples are partitioned based on corporate governance (Panel A), information evaluation (Panel B), and corporate ownership (Panel C). Sample period spans from January 2014 to June 2022. The raw excess returns of control stocks, treated stocks, and the return differences with the corresponding t-statistics in parentheses are reported. Standard errors are adjusted with Newey and West (1987) five lag correction. ***/**/* indicate the significant returns at the 1%, 5% and 10% confidence level, respectively.

	Control	**Treated**	**Diff**	**Control**	**Treated**	**Diff**
Panel A	**Loose Governance**			**Strict Governance**		
Investment	0.181**	0.072	**-0.109**	0.139*	0.141*	0.002
	(2.487)	(1.014)	**(-1.336)**	(1.875)	(1.915)	(0.021)
Past return	0.281	0.398**	0.117	0.358*	0.379**	0.021
	(1.525)	(1.994)	(0.704)	(1.848)	(1.996)	(0.102)
Profitability	0.457***	0.222**	**-0.235****	0.369***	0.320**	-0.049
	(3.979)	(2.136)	**(-2.178)**	(3.010)	(2.560)	(-0.521)
Risk	0.241	0.592**	0.351*	0.27	0.312	0.041
	(0.802)	(2.044)	(1.755)	(0.886)	(0.989)	(0.211)
Trading friction	0.759***	0.374*	**-0.386*****	0.780***	0.599***	-0.181
	(3.734)	(1.729)	**(-2.656)**	(3.622)	(3.333)	(-1.170)
Value	0.689***	0.517**	**-0.172**	0.737***	0.726**	-0.011
	(2.858)	(2.499)	**(-0.959)**	(2.666)	(2.571)	(-0.052)
Panel B	**Low Evaluation**			**High Evaluation**		
Investment	-0.035	0.424*	0.459	0.111	0.084	-0.027
	(-0.189)	(1.981)	(1.366)	(1.646)	(1.327)	(-0.307)
Past return	0.487*	0.63	0.143	0.328*	0.429**	0.101
	(1.802)	(1.387)	(0.289)	(1.729)	(2.287)	(0.611)
Profitability	0.701***	0.528**	**-0.173**	0.257**	0.210**	-0.047
	(3.773)	(2.196)	**(-0.673)**	(2.297)	(2.465)	(-0.477)
Risk	0.581	-0.131	**-0.712**	0.146	0.384	0.237
	(1.619)	(-0.253)	**(-1.491)**	(0.448)	(1.157)	(1.240)
Trading friction	1.176***	0.345	**-0.831****	0.654***	0.455**	-0.198
	(3.811)	(0.856)	**(-2.399)**	(2.957)	(2.112)	(-1.477)
Value	1.174***	1.127***	-0.047	0.402*	0.32	-0.081
	(3.429)	(2.632)	(-0.111)	(1.856)	(1.555)	(-0.515)
Panel C	**Non-SOE**			**SOE**		
Investment	0.199***	0.089	**-0.110**	-0.049	0.097*	0.146**
	(3.016)	(1.330)	**(-1.209)**	(-0.701)	(1.709)	(2.032)
Past return	0.392**	0.556***	0.165	0.315	0.32	0.005
	(2.149)	(3.146)	(0.963)	(1.397)	(1.380)	(0.028)
Profitability	0.355***	0.134	**-0.221****	0.348***	0.310***	-0.038
	(2.898)	(1.122)	**(-2.129)**	(3.202)	(2.967)	(-0.370)
Risk	0.138	0.495	0.356**	0.448	0.558*	0.109
	(0.425)	(1.531)	(2.009)	(1.564)	(1.910)	(0.411)
Trading friction	0.731***	0.609***	-0.121	0.690***	0.321	**-0.369****
	(3.278)	(3.000)	(-0.718)	(3.470)	(1.527)	**(-2.288)**
Value	0.619**	0.502*	**-0.117**	0.476**	0.509**	0.033
	(2.299)	(1.873)	**(-0.536)**	(2.204)	(2.268)	(0.179)

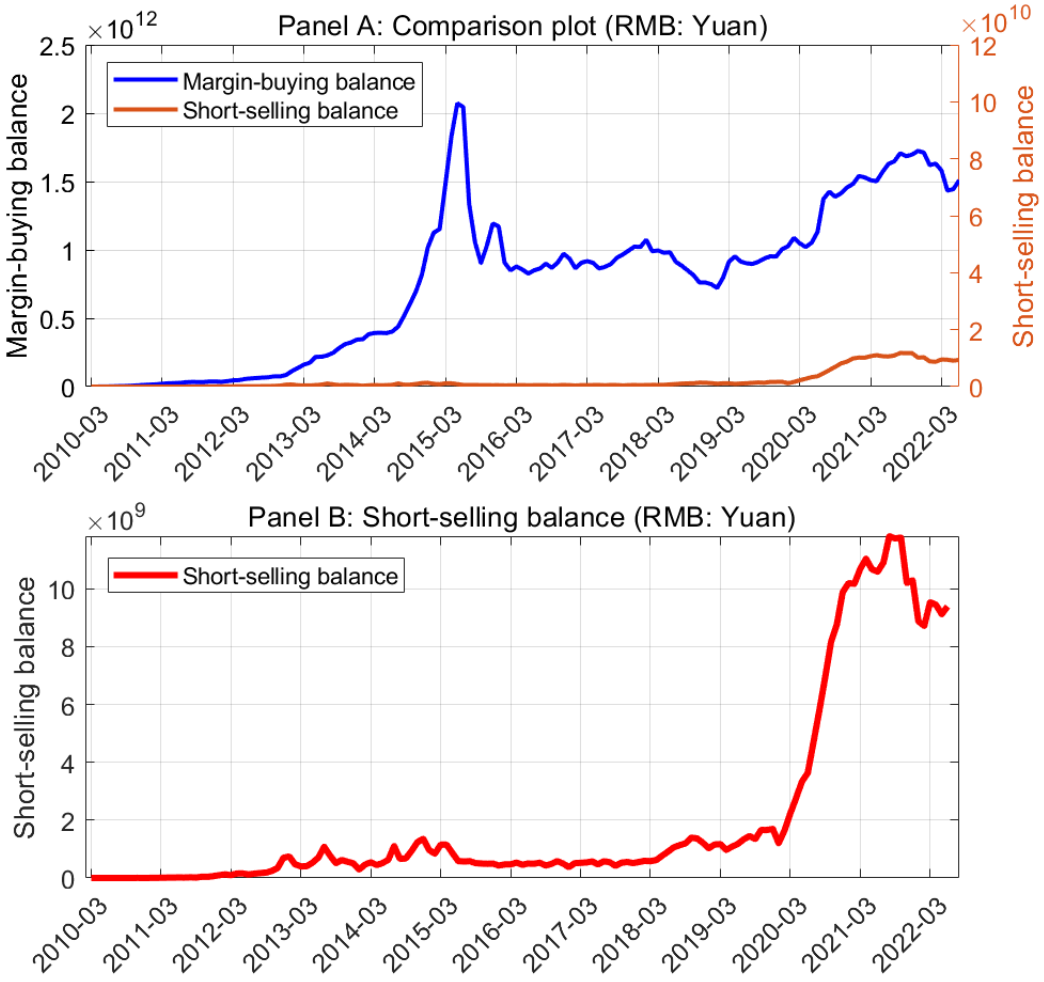


Figure 1: The development of short-selling activities in China

Panel A of this figure plots monthly trend of short-selling balance and margin-buying balance. Panel B of this figure plots monthly trends of short-selling balance in the whole A-share market. The data are from CSMAR.

Internet Appendix

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(not for publication)

Table A1: Requirements for the designated stocks

According to "The Implementation of Exchange Rules for Short-Selling and Margin-Trading Stocks" issued by the Shanghai and Shenzhen stock exchanges, the designated stocks shall meet the following requirements:

	Requirements for the designated stocks
1	Listed and traded on the Exchange for no less than three months.
2	The outstanding share of the stock purchased on margin (shorted) shall not be less than 100 (200) million or the outstanding market capitalization shall not be less than 500 (800) million yuan.
3	The number of shareholders shall not be less than 4,000.
4	The average daily turnover rate shall not be less than 15% of the benchmark index within the recent three months.
5	The average daily trading amount shall not be less than 50 million yuan within the recent three months.
6	The average return deviation shall not be more than 4% of the benchmark index.
7	The stock is not subject to risk warning or other forbidden conditions from the Exchange.

Table A2: Definitions of firm characteristics

This table describes detailed definitions for firm characteristics.

No.	Acronym	Stock Characteristics Definition	Data Source	Frequency	Literature
1	acc	acc = [(Δ CA - Δ CASH) - (Δ CL - Δ STD - Δ TP) - Dep]/ Total Assets; where Δ represents the difference between two consecutive periods, CA, CASH, CL, STD, TP and Dep denote current assets, cash/cash equivalents, current liabilities, non-current liabilities due within one year, notes payable, income tax payable, depreciation and amortization expense, respectively.	CSMAR	Semi-annual	Sloan, 1996
2	absacc	Absolute value of acc.	CSMAR	Semi-annual	Bandyopadhyay, Huang and Wirjanto, 2010
3	abturn	The ratio of its average daily share turnover within month t to its average daily share turnover over the past 12 months/ A firm's abnormal turnover is calculated as the ratio of its average daily turnover over the past 20 days to its average daily turnover over the past 250 days. A firm's daily turnover is calculated as its share trading volume divided by its total shares outstanding.	WIND	Monthly	Liu, Stambaugh, and Yu, 2019
4	Mo12turn	The average daily share turnover over the past 250 days. A firm's daily turnover is calculated as its share trading volume divided by its total shares outstanding.	WIND	Monthly	Liu, Stambaugh, and Yu, 2019
5	agr	Annual percent change in total assets.	CSMAR	Annual	Hou, Xue, and Zhang, 2015; Fama and French, 2015
6	beta	Estimated market beta from weekly excess returns and value weighted market excess returns for 3 years ending month t-1 with at least 52 weeks of returns.	WIND	Monthly	Fama and MacBeth, 1973
7	idiovol	Standard deviation of residuals of weekly excess returns on weekly value weighted market excess returns for 3 years prior to month end(ending in month t-1).	WIND	Monthly	Ali, Hwang and Trombley, 2003
8	betadimson	CAPM beta is estimated using the past 12 months(month t-11 through t, inclusive) of daily excess returns with a five-lag Dimson (1979) correction.	WIND	Monthly	Dimson, 1979
9	bm	Book value of equity divided by month-end market capitalization, where book value of equity is defined as total shareholders' equity excluding minority interests, and market capitalization as close price multiplied by total shares. We use total shares in calculating value evaluation.	CSMAR, WIND	Monthly	Fama and French, 2015; Liu, Stambaugh, and Yu, 2019
10	cash	Cash and cash equivalents divided by average total assets(quater t and t-1).	CSMAR	Quarterly	Palazzo, 2012
11	cashdebt	Earnings divided by total liabilities.	CSMAR, WIND	Quarterly	Ou and Penman, 1989
12	cashspr	Quarter-end market capitalization plus long-term debt minus total assets divided by cash and equivalents.	CSMAR	Quarterly	Chandrashekar and Rao, 2006
13	cfp	Operating cash flows divided by quarter-end market capitalization.	CSMAR	Quarterly	Desai, Rajgopal, and Venkatachalam, 2004
14	chato	Change in sales divided by average total assets.	CSMAR	Quarterly	Soliman, 2008
15	chinv	Change in inventory scaled by total assets.	CSMAR	Quarterly	Thomas and Zhang, 2002
16	chmom	Cumulative returns from months t-6 to t-1 minus months t-12 to t-7.	WIND	Monthly	Gettleman and Marks, 2006
17	chpm	Change in income before extraordinary items scaled by sales.	CSMAR, WIND	Quarterly	Soliman, 2008
18	chtx	Percent change in taxes from quarter t-1 to t.	CSMAR	Quarterly	Thomas and Zhang, 2011

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No.	Acronym	Stock Characteristics Definition	Data Source	Frequency	Literature
19	cp	Cash flow equals the net change in cash or cash equivalents between the two most recent cash flow statements. A stock's CP is the ratio of cash flow to the product of last month-end's close price and total shares. We use total shares in calculating value evaluation.	CSMAR, WIND	Monthly	Liu, Stambaugh, and Yu, 2019
20	dolvol	Natural logarithm of trading volume times price per share from month t-2.	WIND	Monthly	Chordia, Subrahmanyam, and Anshuman, 2001
21	ear	Sum of daily returns in three days around earnings announcement.	WIND	Quarterly	Kishore, Brandt, Santa-Clara, and Venkatachalam, 2008
22	egr	Quarterly percentage change in book value of equity.	CSMAR	Quarterly	Richardson, Sloan, Soliman, and Tuna, 2005
23	ep	The earnings-to-price ratio. The earnings is calculated as the most recently reported net profit excluding nonrecurrent gains/losses in the most recently reported quarterly statement. The market capitalization for value evaluation is based on outstanding A-share, B-shares, H-shares, and non-tradable shares. EP is the ratio of earnings to the product of last month-end's close price and total shares.	WIND	Quarterly	Liu, Stambaugh, and Yu, 2019
24	fscore	The composite score, F, is the sum of the individual binary signals: Fscore = Froa + Fdroa + Fcf/a + Facc + Fdmargin + Fdturn + Fdlever + Fdliquid. For the sake of simplicity, we refer readers to the Appendix B. of Hou, Qiao and Zhang(2020, WP) for more details.	CSMAR	Quarterly	Piotroski, 2000; Hou, Qiao and Zhang, 2020
25	gma	Revenue minus cost of goods sold divided by lagged total assets.	CSMAR	Quarterly	Novy-Marx, 2013
26	grCAPX	Percent change in capital expenditures from year t-1/2 to year t.	CSMAR	Semi-annual	Anderson and Garcia-Feijoo, 2006
27	herf	Sum of squared percent sales in industry for each company.	CSMAR	Quarterly	Hou and Robinson, 2006
28	hire	Percent change in number of employees.	CSMAR	Annual	Bazdresch, Belo and Lin, 2014
29	ill	Average of daily (absolute return/RMB volume)*1,000,000 in month t.	WIND	Monthly	Amihud, 2002
30	invest	The sum of annual change in fixed assets and annual change in inventories divided by lagged total assets.	CSMAR	Annual	Chen and Zhang, 2010
31	lev	Total liabilities divided by quarter-end market capitalization.	CSMAR, WIND	Quarterly	Bhandari, 1988
32	lgr	Quarterly percent change in total liabilities.	CSMAR	Quarterly	Richardson, Sloan, Soliman and Tuna, 2005
33	lm	[(Number of volumes¡150000 in month t-1) + (1/sum of daily turnover in month t-1)/deflator]*(21/NoTD), where NoTD is the total number of trading days over the month t-1, and deflator is maxTurnover in month t-1+1 for all stocks in each month.	WIND	Monthly	Liu, 2006; Hou, Qiao and Zhang, 2023
34	maxret	Maximum daily return from returns during month t-1.	WIND	Monthly	Bali, Cakici and Whitelaw, 2011
35	maxret2	Following Liu,Stambaugh and Yu(2019), maximum daily return from returns during month t.	WIND	Monthly	Liu, Stambaugh, and Yu, 2019
36	mom12m	11-month cumulative returns ending one month before month end(month t-12 to month t-1).	WIND	Monthly	Jegadeesh, 1990
37	mom1m	1-month cumulative return(month t).	WIND	Monthly	Jegadeesh and Titman, 1993
38	mom6m	5-month cumulative returns ending one month before month end(month t-6 to month t-1).	WIND	Monthly	Jegadeesh and Titman, 1993
39	mom36m	Cumulative returns from months t-36 to t-13.	WIND	Monthly	Jegadeesh and Titman, 1993
40	mve	The natural log of market capitalization at end of month t-1. Specifically, size is the previous month's closing price times total A shares outstanding, including non-tradable shares.	WIND	Monthly	Liu, Stambaugh, and Yu, 2019

Continued on next page

No.	Acronym	Stock Characteristics Definition	Data Source	Frequency	Literature
41	noa	(Operating asset - Operating liability)/lagged Total asset. Operating asset equals total assets minus cash and short-term investment, and Operating liability equals total assets minus short-term debt, long-term debt, minority interest, book preferred stock, and book common equity.	CSMAR	Quarterly	Liu, Stambaugh, and Yu, 2019
42	operprof	Quarterly operating profit divided by lagged common shareholders' equity (total shareholders' equity excluding minority interests).	CSMAR	Quarterly	Leippold, Qian and Zhou, 2022
43	op	Operating revenue minus cost of goods sold, interest expense, selling expense, general and administrative expense, all divided by the common shareholders' equity (the total shareholders' equity excluding minority interests).	CSMAR	Quarterly	Fama and French, 2015
44	oscore	O = -1.320 - 0.407 log(TA) + 6.03 TLTA - 1.430 WCTA + 0.076 CLCA - 1.720 OENEG - 2.370 NITA - 1.830 FUTL + 0.285 IN2 - 0.521 CHIN. For the sake of space, please refer to the Appendix B. of Hou, Qiao and Zhang (2023) for more details.	CSMAR, WIND	Quarterly	Ohlson, 1980
45	pchgm_pchsale	Percentage change in gross margin minus percentage change in sales.	CSMAR	Quarterly	Abarbanell and Bushee, 1998
46	pchquick	Percentage change in quick ratio.	CSMAR	Quarterly	Ou and Penman, 1989
47	pchsale_pchrect	Quarterly percentage change in sales minus quarterly percentage change in receivables.	CSMAR	Quarterly	Abarbanell and Bushee, 1998
48	pchsale_pchxsga	Quarterly percentage change in sales minus quarterly percentage change in management expenses.	CSMAR	Quarterly	Abarbanell and Bushee, 1998
49	pchsaleinv	Quarterly percentage change in sales-to-inventory.	CSMAR	Quarterly	Ou and Penman, 1989
50	pctacc	Same as acc except that the numerator is divided by the absolute value of net income; if net income = 0 then net income set to 0.01 for denominator.	CSMAR	Semi-annual	Hafzalla, Lundholm and VanWinkle, 2011
51	quick	Quick ratio, (current assets - inventory) / current liabilities.	CSMAR	Quarterly	Ou and Penman, 1989
52	roaq	Income before extraordinary items divided by one quarter lagged total assets.	CSMAR, WIND	Quarterly	Balakrishnan, Bartov, and Faurel, 2010
53	roe	The ratio of a firm's earnings to book equity, where book equity is defined as total shareholders' equity excluding minority interests.	CSMAR	Quarterly	Liu, Stambaugh, and Yu, 2019
54	roeq	Income before extraordinary items divided by lagged common shareholders' equity.	CSMAR	Quarterly	Hou, Xue, and Zhang, 2015
55	roc	EBIT/(Net working capital + Net fixed assets)	CSMAR	Quarterly	Brown and Rowe, 2007
56	roic	EBIT/Enterprise Value(ceq+lt-che)	CSMAR, WIND	Quarterly	Brown and Rowe, 2007
57	rsup	Sales from quarter t minus sales from quarter t-1 divided by quarter-end market capitalization.	CSMAR	Quarterly	Kama, 2009
58	salecash	Quarterly sales divided by cash and cash equivalents.	CSMAR	Quarterly	Ou and Penman, 1989
59	saleinv	Quarterly sales divided by total inventory.	CSMAR	Quarterly	Ou and Penman, 1989
60	salerev	Quarterly sales divided by accounts receivable.	CSMAR	Quarterly	Ou and Penman, 1989
61	sgr	Quarterly percentage change in sales.	CSMAR	Quarterly	Lakonishok, Shleifer, and Vishny, 1994
62	skewness	Skewness of a stock's daily returns from month t.	WIND	Monthly	Hou, Xue, and Zhang, 2019
63	sp	Quarterly sales divided by quarter-end market capitalization.	CSMAR	Quarterly	Barbee, Mukherji, and Raines, 1996
64	std_turn	Monthly standard deviation of daily share turnover in month t. Daily share turnover is defined as daily trading volume scaled by daily shares outstanding.	WIND	Monthly	Chordia, Subrahmanyam, and Anshuman, 2001
65	tang	(Cash holdings + 0.715*receivables + 0.547*inventory + 0.535*fixed assets)/total assets.	CSMAR	Quarterly	Almeida and Campello, 2007
66	tb	Tax income, defined as net income plus income expense, divided by net income.	CSMAR, WIND	Quarterly	Lev and Nissim, 2004
67	turn	Average monthly trading volume for month t-3 to t-1 scaled by number of shares outstanding in month t.	WIND	Monthly	Datar, Naik, and Radcliffe, 1998
68	volatility	The standard deviation of daily returns from month t-1.	WIND	Monthly	Ang, Hodrick, Xing, and Zhang, 2006
69	volatility2	The standard deviation of daily returns from month t.	WIND	Quarterly	Ang, Hodrick, Xing, and Zhang, 2006

Table A3: Groups of characteristics

This table categorizes all the firm characteristics into six groups, including investment, past return, profitability, risk, trading friction and value following Leippold, Wang, and Zhou (2022).

Panel A: Investment			
absacc	Absolute accruals	acc	Working capital accruals
chinv	Change in inventory	grCAPX	Growth in capital expenditures
hire	Employee growth rate	invest	Capital expenditures and inventory
lev	Leverage to market capitalization	lgr	Growth in long-term debt
noa	Operating accruals	pctacc	Percent change in accruals
agr	Asset growth rate		
Panel B: Past return			
chmom	Change in 6-month momentum	mom6m	6-month momentum
mom12m	12-month momentum	mom36m	36-month momentum
mom1m	1-month momentum		
Panel C: Profitability			
cash	Cash to total assets	cashdebt	Earnings to total liabilities
cashspr	Cash productivity	chpm	Change in profit margin
chato	Change in asset turnover	fscore	Composite F score
chtx	Change in tax expense	oscore	Ohlson's O-score
gma	Gross profitability	pchquick	Percent change in quick ratio
pchgm_pchsale	Percent change in gross margin - percent change in sales	pchsale_pchxsga	Percent change in sales - percent change in SG&A
pchsale_pchrect	Percent change in sales - percent change in A/R	quick	Quick ratio
pchsaleinv	Percent change in sales-to-inventory	salecash	Sales to cash
rsup	Revenue surprise	salerev	Sales to inventory
saleinv	Sales to receivables	tb	Tax income to book income
tang	Debt capacity/firm tangibility		
Panel D: Risk			
beta	CAPM market beta	betadimson	Dimson-adjusted CAPM market beta
idiovol	Idiosyncratic return volatility	skewness	Skewness of a stock's daily returns
volatility	Volatility of daily return at month t-1	volatility2	Volatility of daily return at month t
Panel E: Trading frictions			
abturn	One month abnormal turnover	maxret	Maximum daily return at month t-1
mo12turn	Average daily share turnover	maxret2	Maximum daily return at month t
herf	Industry sales concentration	mve	Market capitalization
dolvol	Yuan trading volume	std_turn	Standard deviation of daily share turnover
ear	Earnings announcement return	turn	Share turnover
ill	Standard deviation of residuals	lm	Turnover-adjusted number of zero daily trading volume
Panel F: Value			
bm	Book-to-market equity	operprof	Quarterly operating profit to common shareholders' equity
cfp	Operating cash flows to market capitalization	op	Operating profitability to market capitalization
cp	Cash to market capitalization	roaq	Return on assets
egr	Growth in common shareholder equity	roe	Earnings to book equity
sgr	Sales growth	roeq	Earnings to lagged book equity
ep	Earnings to market capitalization	roc	Return on capital
sp	Leverage to market capitalization	roic	Return on invested capital

Table A4: The Fama and MacBeth (1973) regression analysis on the qualification effect

This table reports Fama and MacBeth (1973) regression analysis of the qualification effect on stock returns. Standard errors are adjusted with Newey and West (1987) five lag correction. ***/**/* indicate the significant at 1%, 5% and 10% confidence level, respectively.

	(1)	(2)	(3)	(4)	(5)
Treat × Post	**-0.011**	**0.010**	**-0.005**	**-0.064**	**0.042**
	(-0.068)	**(0.066)**	**(-0.037)**	**(-0.616)**	**(0.396)**
Size		-0.057	-0.214	-0.219	-0.365**
		(-0.342)	(-1.449)	(-1.477)	(-2.381)
B/M			0.344	0.086	-0.036
			(0.498)	(0.161)	(-0.069)
ROE			14.816***	14.210***	13.932***
			(5.549)	(5.647)	(5.649)
Beta				-0.164	-0.066
				(-0.376)	(-0.154)
Ivol				-0.104	-0.047
				(-1.470)	(-0.709)
Mom1m				-3.867***	-3.992***
				(-3.184)	(-3.289)
Turnover					-2.074***
					(-3.313)
Intercept	0.730	1.925	5.163	5.915	9.295**
	(1.105)	(0.461)	(1.336)	(1.586)	(2.419)
Adjusted R-squared	0.007	0.017	0.056	0.099	0.106

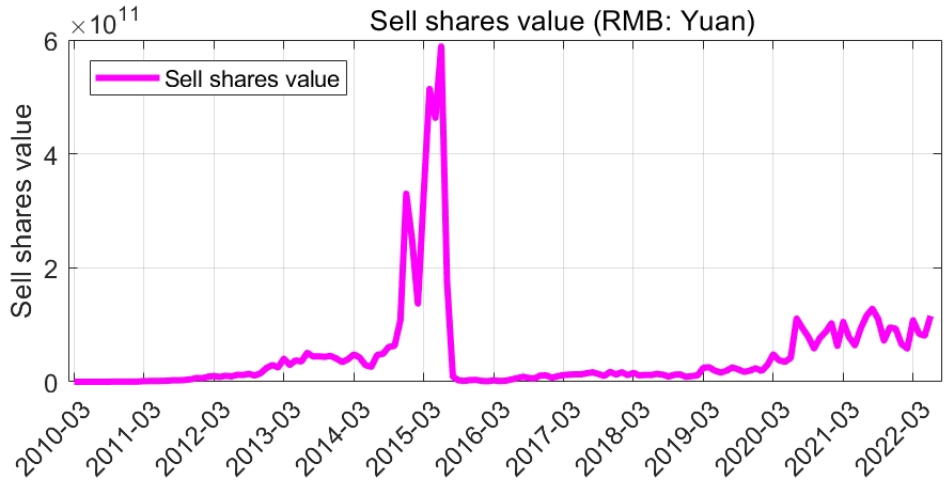


Figure A1: The sell share value of short-selling activities

This figure plots monthly sell share value (measured in RMB) from March 1, 2010 to March 31, 2022. Data are from CSMAR.

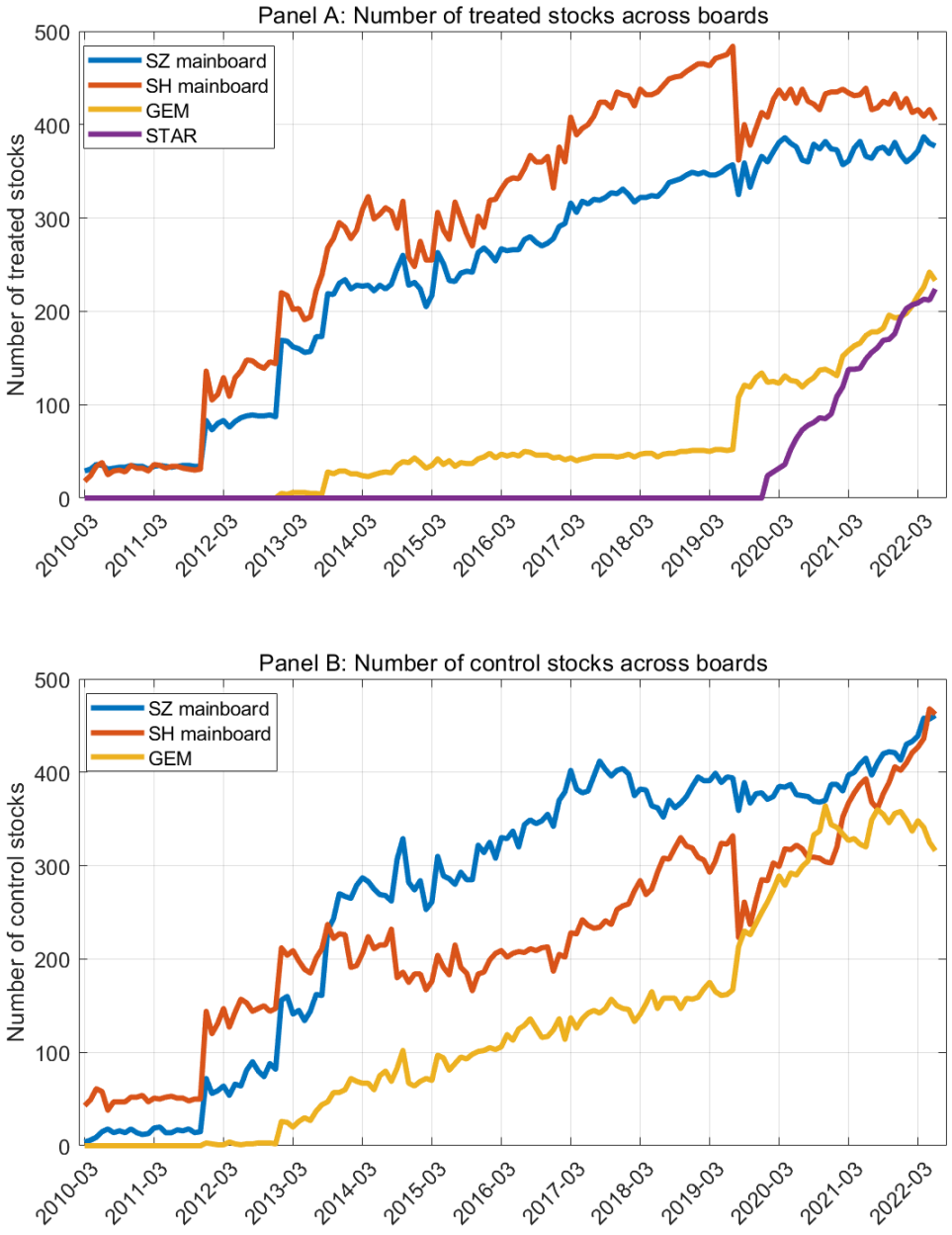


Figure A2: Distribution of sample stocks

This figure plots monthly distribution of sample stocks across boards. Panel A (B) plots distribution of treated stocks (control stocks).

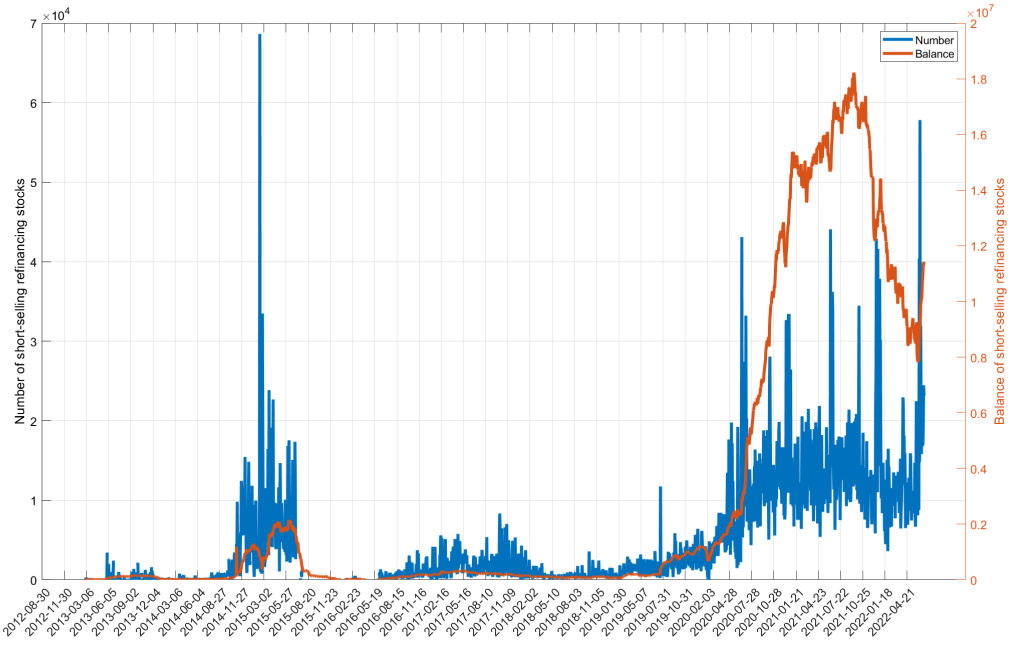


Figure A3: The development of short-selling refinancing program

This figure plots daily amount of lendable shares and transaction volume of short-selling refinancing program from August 30, 2012 to June 30, 2022. Data are from CSMAR.

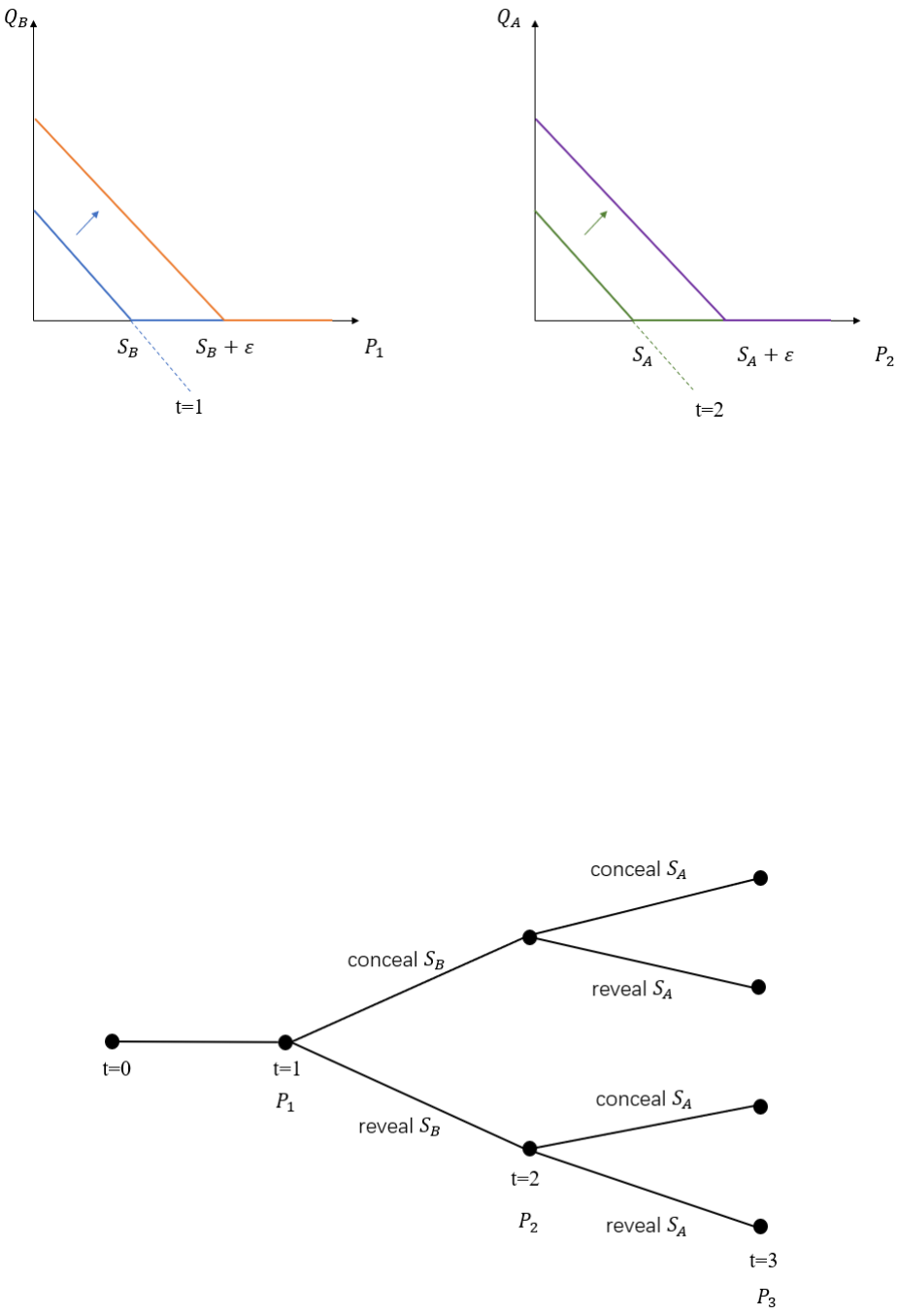


Figure A4: The upper plot shows the demand curves for investor A and B, and the bottom plot shows the decision tree at different stages.