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Do Short Sales Reduce Post-Shock Anomalies in Stock Prices? Evidence from the Chinese Stock Market †

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Abstract: This study investigates the role of short sales in mitigating post-shock anomalies in stock returns within the context of China's evolving short-sales regulations. Utilizing a unique dataset of daily short-sale volumes, this research examines how short sellers influence stock price behavior following significant price shocks. The findings reveal that short sellers act as informed arbitragers, reducing post-shock anomalies, particularly in news-driven events, and supporting Diamond and Verrecchia's hypothesis that short-sale constraints slow price adjustments to information. This study fills a critical gap in the literature, offering insights into price efficiency and implications for regulators and investors. By highlighting the unintended consequences of restrictive short-sale policies, this paper recommends reforms to reduce borrowing costs, enhance lending programs, and promote effective short-selling practices. These results contribute to the broader understanding of market dynamics, particularly in emerging markets with tight short-sale restrictions like China.

Keywords: price shocks; short sales; predictability of stock returns; short restriction; price efficiency

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1. Introduction

The prolonged bearish stock market conditions since the mid-COVID-19 pandemic in China have led to another round of tightening short-sale regulations by the Chinese Securities Regulatory Commission (CSRC). These regulations, including the suspension of the China Securities Finance Corporation's (CSFC) securities loan program and increased deposit requirements for short sellers, have further constrained short-selling activities. Against this backdrop, the role of short sales in a bearish market and their informational impact on stock price behavior are under intense scrutiny. This paper seeks to address a critical gap in understanding the implications of short sales in influencing stock returns following significant price shocks.

A large body of the finance literature has examined post-shock patterns in stock returns, often interpreted as evidence of investor biases in processing information (De Bondt & Thaler, 1985). These patterns challenge the efficient market hypothesis (Fama, 1970), yet non-behavioral factors such as bid–ask bounces (Atkins & Dyl, 1990; Cox & Peterson, 1994), non-trading (Lo & MacKinlay, 1990), and market liquidity (Lasfer et al., 2003; Mazouz et al., 2012) also contribute to the anomalies. Despite these insights, the role of short sales as a potential explanatory factor remains underexplored. Prior studies (Otchere & Chan, 2003; Savor, 2012) have hinted at the influence of short sales on post-shock patterns, and Frank and Sanati (2018) noted the impact of short-sale constraints on arbitrage activity. However, there is insufficient empirical evidence explicitly linking short-selling activity to the persistence or reduction of post-shock anomalies.

Addressing this gap is vital for understanding the dynamics of stock price adjustments following significant shocks, especially in markets like China where short-sale regulations have undergone notable changes. This study is motivated by the unique features of the Chinese stock market, where a historical ban on short selling evolved into a pilot program allowing selective short sales. The availability of granular data on daily short-sale volumes enables an in-depth examination of short sellers' behaviors and their impacts on post-shock stock returns.

The findings of this study have significant implications. By demonstrating that short sellers act as informed arbitragers and mitigate the overreaction to price shocks, this research contributes to the literature on price efficiency and market dynamics. Additionally, it informs regulators about the unintended consequences of restrictive short-sale policies and highlights the need for reforms to reduce borrowing costs, enhance lending programs, and foster effective short selling. This study also contributes to the literature by focusing on an emerging market context, offering insights into how evolving regulatory frameworks influence price efficiency. Unlike developed markets, China provides a distinctive setting to explore short sales under restrictive policies, advancing our understanding of market dynamics in similar emerging markets.

This paper also provides evidence supporting the hypothesis of Diamond and Verrecchia (1987) that short-sale constraints slow price adjustments to information. It further contributes to the ongoing debate on whether short sellers improve or destabilize stock price efficiency. By introducing a price event modeling framework that incorporates short-sale ability and intensity, this study reveals that short sellers' trading activities reduce the magnitude of post-shock anomalies, particularly in response to news-driven events.

Ultimately, this research fills a critical gap in understanding the informational role of short sales, particularly in the context of China's evolving regulatory environment. It offers new insights into the mechanisms driving post-shock stock returns and provides actionable recommendations for policymakers, practitioners, and investors seeking to navigate and optimize their strategies in the face of significant price shocks.

The remainder of the paper is organized as follows: the next section provides an introduction to short sales in mainland China; Section 3 describes the data and methodology; Section 4 shows descriptive statistics; Sections 5 and 6 present and discuss the results; and Section 7 concludes.

2. Short Sales in Mainland China

In March 2010, China's SEC launched a pilot program aimed at relaxing short-selling restrictions for a specific set of stocks. Initially, this list included 90 prominent stocks chosen based on their market capitalization and liquidity. Subsequent adjustments were made to include more constituent stocks from major market indexes. By the end of May 2018, the list had grown to encompass 972 stocks[1], accounting for approximately 80% of the market capitalization of publicly traded shares on mainland China's stock market.

Short-selling constraints for individual traders in mainland China have been notably stringent. Initially, only shares held by securities brokerage companies were available for lending. This changed in October 2011 when securities firms gained the ability to borrow shares from funds, insurance companies, and other certified financial institutions for their clients engaging in short selling (Chinese Securities Regulatory Commission, 2011). Additionally, prospective short sellers are required to maintain an initial margin of at least 500,000 RMB, an increase from the previous 100,000 RMB, and must have over six months of securities trading experience. Brokerage firms can set even stricter criteria. Notably, the borrowing interest rate for retail securities accounts holding a short position has consistently been set above 10% (Chang et al., 2013), a rate that is significantly higher than the typical cost in the U.S. stock market (Acadian Asset Management, n.d.). Furthermore, daily public disclosure of all short sellers' transactions, including the volume and value of their trades, is mandatory. Practices like naked short sales are strictly prohibited, and the uptick rule is enforced

Short sellers typically borrow shares from securities companies, which can fulfill the requests using their own inventories or route the orders to the China Securities Finance Corporation (CSF) for third-party lenders. Consequently, shares held by securities companies and other financial institutions participating in the CSFC's securities loan program are considered lendable shares. It is important to note that new short positions cannot be closed on the same day, ensuring that the event-day short volume accurately reflects short sellers' response to the event.

3. Data and Methodology

3.1. Sample Period

To closely examine the behaviors of post-shock stock prices and short-sale trades around unexpected price shocks, my analysis focuses on daily stock returns. The study period spans from May 2016 to April 2023, a timeframe chosen for its representativeness and robustness in capturing diverse market conditions, including periods of relative stability, elevated volatility, and regulatory changes. This period also covers significant global events, including the COVID-19 pandemic, which had substantial impacts on stock markets worldwide.

Daily returns are calculated as the percentage change in closing prices, adjusted for dividends and stock splits. The corresponding abnormal return is defined as the daily return minus expected returns computed using the Fama and French three-factor model (Fama & French, 1993). This model for calculating abnormal returns is chosen to be consistent with Savor (2012).[2] Model coefficients are estimated over a 250-day window $[t - 270, t - 21]$ prior to the shock day t, with the CSI All Share Index serving as the market portfolio index. Stock price data are sourced from the Wind data terminal.[3]

The chosen period ensures the inclusion of diverse market dynamics, such as the ongoing market reforms in mainland China and the recovery phase after the 2015–2016 Chinese stock market turbulence. Furthermore, this period captures the market's response to the COVID-19 pandemic (January 2020 to early 2022), enabling an analysis of price events during one of the most volatile market periods in recent history. While the study does not exclude price events during the COVID-19 period, it adopts measures to exclude price-clustering dates—days where extreme market-wide shocks led to abnormal returns across most stocks.[4] For instance, significant market sell-offs in early 2020 caused by the initial pandemic outbreak are filtered to prevent distortions in individual stock-level event identification. This approach ensures that the price event pool reflects idiosyncratic shocks rather than systemic market-wide movements.

3.2. Price Events

To classify significant price events, each observation day's abnormal return is compared to the average abnormal return calculated from its respective estimation window. If the absolute difference surpasses three standard deviations from the estimation window, the observation is identified as an extreme abnormal price movement, or a "price event". This method requires a minimum of 540 valid historical trading days (270 for calculating the first abnormal return and another 270 for determining a price event), thereby excluding IPO days.

Events generated by stocks with a negative book value and ST/ST* stocks are excluded, as are stock price events coinciding with a market portfolio index shock exceeding three standard deviations during the estimation window.[5] This filtering step is crucial to mitigate the impact of market-wide turbulence, such as extreme sell-offs or rallies, ensuring that the selected price events reflect stock-specific movements rather than broader market conditions.

While prior studies often use fixed thresholds like a 10% daily price change to define price events (e.g., Larson & Madura, 2003; Savor, 2012),[6] I adopt a volatility-relative approach for two key reasons. First, empirical evidence highlights that stock market volatility shifts over time (e.g., Schwert, 1989; Diamandis, 2008), meaning that fixed thresholds could disproportionately include or exclude events during periods of high or low volatility. Second, fixed thresholds are less suitable for markets like mainland China, where daily price limits could mask large relative price movements. My volatility-relative definition aligns with methods used by Pritamani and Singal (2001), Lasfer et al. (2003), and Boehmer and Wu (2013).

3.3. Additional Filters and Final Sample

To ensure a robust event selection, I apply additional criteria:

(a) Resume-trading exclusions—events from stocks on resume-trading days following a suspension of more than a week are excluded, as their price dynamics differ from typical trading patterns;
(b) Thin trading and bid-ask bounce exclusions—events from stocks with estimation window standard deviations below the first percentile or close prices below 1 RMB are removed to minimize noise;
(c) Event clustering exclusions—to avoid confounding effects between adjacent price events, observations within 10 trading days following a prior event are disregarded.

After applying these filters, the final dataset includes a total of 31,609 price events. Figures 1 and 2 display the distribution of these events by time and industry. Figure 1 shows that price events are reasonably distributed across the sample period, including during the COVID-19 pandemic, and tend to cluster during periods of elevated market volatility without dominance by any single time period. Figure 2 reveals that the Industrial, Consumer Discretionary, and Information Technology sectors account for 45% of the events, while Telecommunications Services contribute only 2.3%. This distribution reflects the actual industrial composition of all listed stocks in mainland China's stock market.[7]

3.4. Information Content

Earlier studies conducted by Pritamani and Singal (2001), Larson and Madura (2003), Tetlock (2010), and Savor (2012) have revealed that the behavior of post-shock returns is conditioned on the information content of the unexpected price shocks. To assess the information content of the gathered price events, I use Wind's comprehensive news archive database. This database encompasses news releases from public companies' boards of directors (e.g., earnings and dividend announcements), regulatory authorities, institutional securities analysts, and financial news media. A price event is categorized as "informed" if at least one news entry elucidating the event is located in the database, and dated on the same day or adjacent days ($t-1$, $t+1$) to the event. Adjacent days are also considered because a news announcement may be released after market close of the previous trade day or, in other scenario, leaked on the event day before its appearance on the media on the next trade day.[8] Conversely, an event lacking such a connection is classified as "uninformed".[9] Following this criterion, a total of 11,481 informed price events are identified.

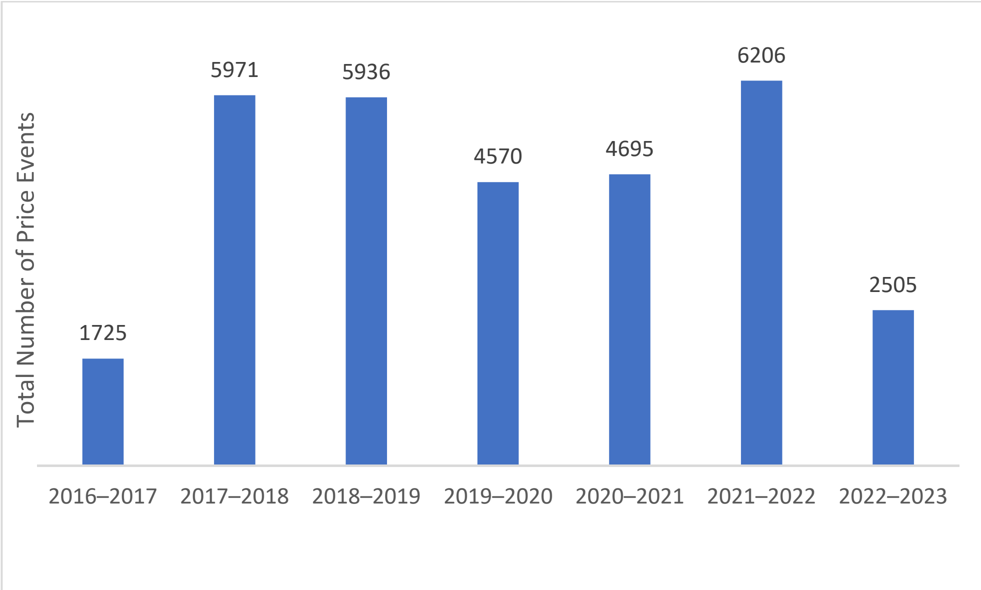

Figure 1. Distribution of price events by year: 1 May 2016–30 April 2023. Notes: A price event is defined as an extreme daily price change that exceeds three standard deviations from its average. The average is calculated based on a 250-day estimation window, ranging from day *t*-21 to *t*-270 prior to the event day *t*. Each annual period in the table starts in May and concludes in April of the subsequent year.

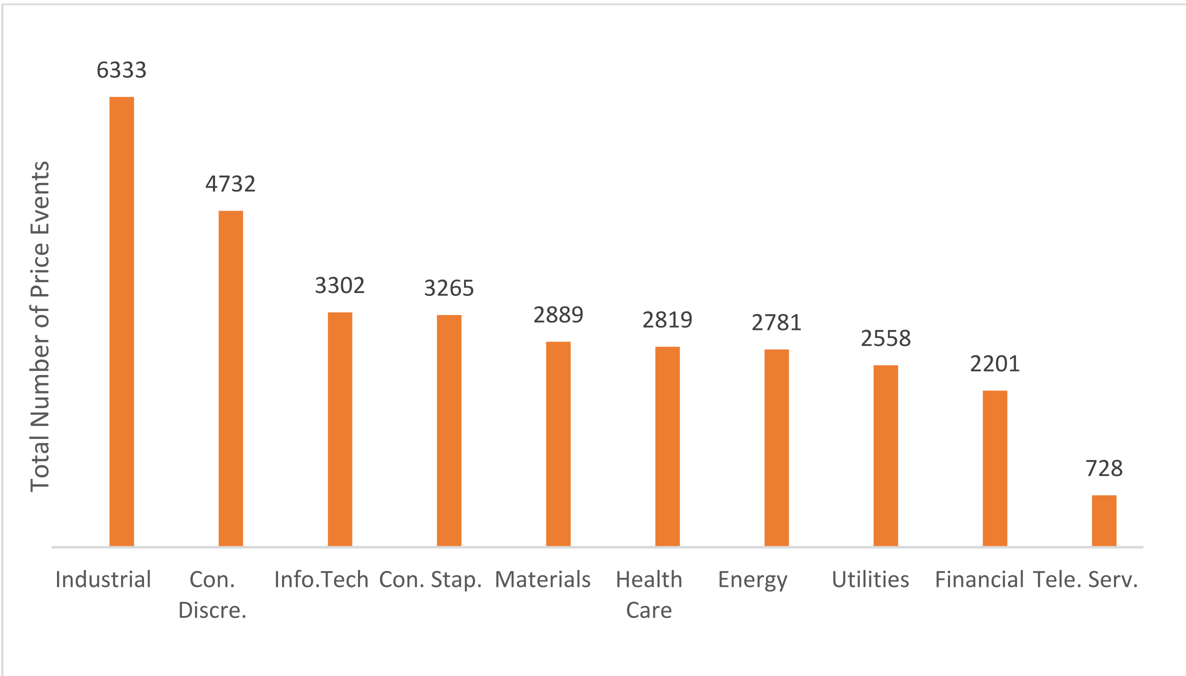

Figure 2. Distribution of price events by industry. Notes: Industry sectors are defined as follows (from left to right): Industrial, Consumer Discretionary, Materials, Financial, Energy, Information Technology, Consumer Staples, Health Care, Utilities, and Telecommunication Services. A price event is defined as an extreme daily price change that is larger than three standard deviations of its average based on the 250-day estimation window from day *t*-21 to *t*-270 prior to the event day *t*.

3.5. Shortable Events and Short-Selling Activities

The price events are initially divided into two subsamples, "shortable" and "non-shortable", with subsample sizes of 10,335 and 21,274, respectively. This division is based on whether the underlying stocks affected by the events were included in the pilot program for short selling at the time of the events, except for instances where the event displayed zero short interest during its estimation timeframe.[10]

The daily short-selling trades associated with each shortable event can be obtained from the webpages of the SSE (Shanghai Stock Exchange) and the SZSE (Shenzhen Stock Exchange). Using these data sources, I calculated the level of short-selling intensity linked to each price event by scaling the event day short-selling volume with the estimated total number of lendable shares based on the event day stock's most recent institutional holder report.[11] This measurement reflects the cost of short selling (Saffi & Sigurdsson, 2011) for a specific stock event observation and provides insights into the assertiveness of short sellers during the event. According to Diamond and Verrecchia's (1987) hypothesis, short-selling trades under a non-prohibited short constraint are likely to be informed.

3.6. The Effect of Removing Short Constraints

Savor (2012) developed a regression model to study the behavior of post-shock returns in relation to earning reports. This model framework can also be used to evaluate the influence of short sales on the dynamics of post-shock adjustments. My first model is defined as follows:

$$CAR_{p,q} = c + \beta_1 AR_0 + \beta_2\,(SE \cdot AR_0) + \gamma' X + u \tag{1}$$

The dependent variable $CAR_{p,q}$ is the post-shock cumulative abnormal return calculated as the sum of daily post-shock abnormal returns over the period $[t + p, t + q]$. The main independent variable AR_0 is the event day $(t + 0)$ abnormal return. SE is an indicator variable for shortable events and c and u are the constant and model error terms, respectively.

The main effect (AR_0) reflects the market's initial reaction to the expected event. The coefficient β_1 reflects the magnitude and the direction of the post-shock adjustment in stock prices for non-shortable price events (De Bondt & Thaler, 1985). The interaction component $(SE \cdot AR_0)$ is used to test whether shortable price events exhibit a different adjustment in post-shock returns as compared to non-shortable ones.

The vector X represents a set of control variables that account for the potential impact of various stock characteristics on cumulative abnormal returns. These characteristics include the price-to-book ratio (PBR), momentum (Mom), log size (LS), event day trading volume (Vol), and the percentage of retail investors (Ret). It is important to note that PBR and LS are measured prior to the event days.

Momentum is the average of daily abnormal returns over a 20-day pre-event window. The trading volume is normalized by the total floating share volume. The retail investor percentage is derived from the event day stock's latest institutional holder report. Previous studies have highlighted the relationship between volume and stock returns (e.g., Campbell et al., 1993; Lee & Swaminathan, 2000; Pritamani & Singal, 2001; Llorente et al., 2002; Tetlock, 2010). The log size and price-to-book ratio are used to control the size and book-to-market effects (Banz, 1981; Rosenberg et al., 1985). The momentum predictor accounts for any information leakage and momentum effects. Frank and Sanati (2018) show that retail trades play a significant role in stock price overreaction to news.

Model (1) is designed to investigate the influence of permitting short sales on the efficiency of stock price adjustments following significant price shocks. According to Diamond and Verrecchia's (1987) hypothesis, the estimate for β_2 is expected to show an opposite sign to that of β_1, implying a reduced post-shock adjustment and thereby indicating greater efficiency in the adjustment process for shortable shares compared to non-shortable ones. Bai and Qin (2015) use a similar model to analyze the impact of short sales on the adjustment of stock price after earning announcement events.[12]

3.7. The Effects of Short-Selling Activities

To analyze the effect of short sales on post-shock abnormal returns, I use a modified version of Savor's regression model. The model is represented as follows:

$$CAR_{p,q} = c + \alpha_1 SS_0 + \alpha_2 (UN \cdot SS_0) + \beta_1 AR_0 + \beta_2 (UN \cdot AR_0) + \gamma' X + u \qquad (2)$$

In this model, SS_0 represents the level of short-sale intensity on the price shock day and is computed as the percentage of the event day short-sale volume relative to the estimated total volume of lendable shares. UN is a binary variable that indicates uninformed events. The control variables are defined in the same manner as in Model (1). The coefficient α_1 captures the impact of short-sale activities on post-shock returns when the price shock is driven by concurrent news, while α_2 reflects any changes in this impact when the price shock is uninformed (absence of news). A significant estimate for α_2 suggests that short sellers are effective at identifying the informational content behind the price shocks. Moreover, if short sellers possess both superior information-processing skills and the ability to capitalize on discrepancies between stock prices and their underlying values, intensified short-sale activities on the event day should correspond with a reduction in post-shock reversals or drifts, if present. Therefore, the interpretation of α_1 and α_2 estimates is contingent upon the observed post-shock pattern revealed by the β_1 and β_2 estimates in Model (2).

4. Descriptive Statistics

Figure 3 illustrates the distinct CAR patterns for positive and negative shocks, highlighting the differences between informed and uninformed shocks. The variable $CAR_{k,10}$ represents the post-shock abnormal return with a holding period starting on the kth day after the event day.[13] In the left plot 3 which depicts the CAR for positive shocks, informed shocks exhibit a sharper decline over time compared to uninformed shocks, reflecting a stronger and faster reversal of overreaction. This suggests that the market corrects the initial price movement of informed shocks more aggressively as it processes the underlying information. In contrast, uninformed shocks in in the left plot show a slower and less pronounced reversal, consistent with their weaker informational content. In the right plot, which presents the CAR for negative shocks, reveals a steady recovery for informed shocks over time, suggesting a gradual adjustment of stock prices to incorporate bad news. The uninformed shocks in the right plot exhibit minimal adjustment, with CAR values remaining close to zero or fluctuating slightly, indicating the absence of significant information content driving these shocks.

Together, these figures underscore the critical role of the information content in driving post-shock return dynamics, with informed shocks showing more substantial and systematic adjustments. The results reveal that positive price shocks lead to reversals, irrespective of their information content, suggesting a market overreaction during such events. This contrasts with Savor's (2012) findings, where an underreaction is linked to informed price shocks, but is consistent with the outcome observed in the study by Frank and Sanati (2018), which identifies investors' overreaction to positive news. For negative shocks, informed events yield negative post-shock returns across all horizons, implying a market underreaction to bad news. In contrast, uninformed negative shocks exhibit a mixed post-shock pattern, with smaller post-shock return magnitudes compared to other scenarios.

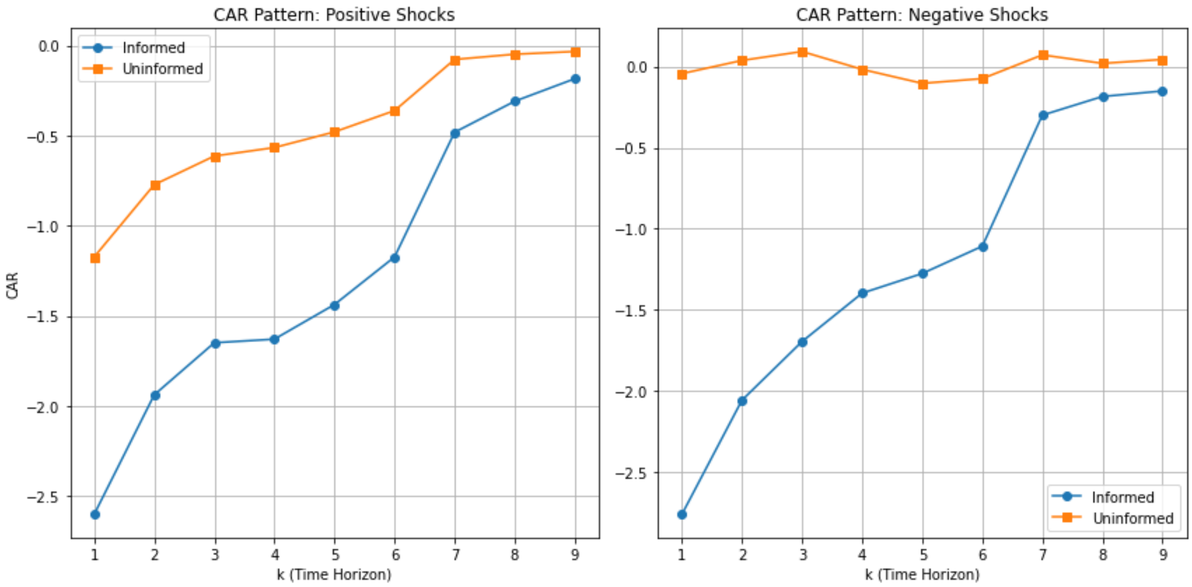

Figure 3. CAR patterns for positive and negative shocks. Note: An abnormal return is defined as the daily return minus expected returns computed using the Fama and French three-factor model. $CAR_{k,10}$ represents the post-shock abnormal return with a holding period starting on the *k*th day after the event day.

Table 1 provides a summary of statistics for the model variables. An important observation from the summary statistics is the significant presence of retail investors within the investor population during the occurrence of price shocks. Frank and Sanati (2018) propose that retail trades amplify overreactions to positive news, as retail investors tend to concentrate on long positions exclusively. Additionally, it is notable that the intensity of short sales is more pronounced in the case of informed shocks compared to uninformed ones. This implies that short sellers exhibit greater activity when price shocks are associated with news.

Table 1. Summary statistics. Note: This table reports the statistics for the event day abnormal return (AR_0), post-shock cumulative abnormal returns ($CAR_{k,10}$, with the holding period starting on the *k*th day after the event day), and short-sale intensity (SS_0) computed as the percentage of event-day short-sale volume relative to the estimated total volume of lendable shares. Other stock characteristic variables, including momentum (*Mom*) calculated as the average of daily abnormal returns over the 20-day pre-event window, price-to-book ratio (*PBR*), the log value of total market capitalization (*logSize*), event day trading volume scaled by the volume of total floating shares, and retail investor percentage (*Ret*). All returns are quoted in percentages. Statistics for SS_0 are calculated based on shortable events only.

	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
		Informed			Uninformed	
Panel A: positive shock ($AR_0 > 0$)						
AR_0	7.643	7.699	1.642	6.867	6.931	1.779
$CAR_{1,10}$	−2.601	−4.081	14.294	−1.173	−2.087	10.254
$CAR_{2,10}$	−1.938	−3.296	11.682	−0.772	−1.592	8.708
$CAR_{3,10}$	−1.649	−2.728	10.701	−0.613	−1.356	8.113
$CAR_{4,10}$	−1.629	−2.650	9.933	−0.566	−1.155	7.597
$CAR_{5,10}$	−1.437	−2.228	9.141	−0.479	−1.059	7.048
$CAR_{6,10}$	−1.173	−1.904	8.433	−0.361	−0.905	6.476
$CAR_{7,10}$	−0.481	−1.055	6.705	−0.077	−0.551	5.382

Table 1. *Cont.*

	Mean	Median Informed	Std. Dev.	Mean	Median Uninformed	Std. Dev.
Panel A: positive shock ($AR_0 > 0$)						
$CAR_{8,10}$	−0.309	−0.852	5.736	−0.048	−0.438	4.673
$CAR_{9,10}$	−0.184	−0.586	4.644	−0.033	−0.360	3.762
MOM	0.550	0.435	1.057	0.206	0.164	0.749
PBR	3.384	2.610	3.477	3.169	2.218	4.473
LS	15.782	15.547	1.045	16.151	15.891	1.263
Vol	0.096	0.078	0.070	0.036	0.028	0.034
Ret	62.242	62.421	24.241	54.435	52.476	23.634
SS_0	1.760	0.234	5.425	0.964	0.156	2.766
Panel B: negative shock ($AR_0 < 0$)						
AR_0	−7.999	−8.124	1.676	−6.840	−6.883	1.899
$CAR_{1,10}$	−2.758	−3.280	13.322	−0.044	−0.621	10.518
$CAR_{2,10}$	−2.055	−2.658	11.048	0.037	−0.652	8.817
$CAR_{3,10}$	−1.694	−2.254	10.149	0.092	−0.530	8.225
$CAR_{4,10}$	−1.396	−1.857	9.440	−0.018	−0.617	7.694
$CAR_{5,10}$	−1.275	−1.747	8.825	−0.104	−0.526	7.122
$CAR_{6,10}$	−1.107	−1.362	8.206	−0.075	−0.456	6.775
$CAR_{7,10}$	−0.300	−0.699	6.716	0.071	−0.417	5.586
$CAR_{8,10}$	−0.185	−0.550	5.756	0.019	−0.430	4.841
$CAR_{9,10}$	−0.151	−0.420	4.677	0.043	−0.320	3.914
MOM	0.832	0.858	1.823	0.327	0.296	1.183
PBR	3.237	2.272	4.616	3.096	2.203	3.931
LS	15.613	15.378	1.055	15.924	15.705	1.137
Vol	0.103	0.089	0.084	0.037	0.031	0.029
Ret	60.558	60.462	24.217	55.665	53.849	23.518
SS_0	1.192	0.094	4.591	0.943	0.074	3.767

5. Empirical Results

This section presents the OLS estimates for both Models (1) and (2). To mitigate heteroscedasticity across diverse price events occurring at different times and involving different stocks, I standardize both event day and post-shock abnormal returns by the corresponding estimation period standard deviations adjusted for forecast errors (Boehmer et al., 1991; Campbell et al., 1997, pp. 158–163). For *t*-statistics, clustered standard errors (clustered by calendar date) are computed (Rogers, 1993). Motivated by preliminary findings revealing asymmetric investor responses to unexpected shocks, I categorize price events based on the direction of the price shock and carry out separate analyses for each category. In contrast to earlier studies focused on identifying post-shock patterns, this paper emphasizes the changes in post-shock patterns, if present, and examines the relationship of those changes with short sales

5.1. The Effect of Allowing Short Sales

Table 2 provides the estimation results from Model (1) for (standardized) cumulative abnormal returns $CAR_{k,10}$, for $k = 1$ to 9, over the 10-day post-shock period. Panels A and B display the estimates for positive and negative informed shocks, respectively.

Table 2. Regression analysis of post-shock returns: the impact of removing short sale bans. Note: This table reports the estimation results for the following regression equation: $CAR_{p,q} = c + \beta_1 AR_0 + \beta_2\,(SE{\cdot}AR_0) + \gamma' X + u$. $CAR_{p,q}$ is the post-shock abnormal return (%) over the holding period [$t + p$, $t + q$]. AR_0 is the event day abnormal return (%). Dummy variable *SE* indicates shortable price events. Vector *X* contains a list of controlling variables: momentum (*Mom*), price-to-book ratio (*PBR*), log size (*LS*), event day scaled trading volume (*Vol*), and the retail investor percentage (*Ret*). Both event day and post-shock abnormal returns are standardized by the corresponding estimation period standard deviations adjusted for forecast errors (see Boehmer et al., 1991; Campbell et al., 1997, pp. 158–163). The *t*-test statistics, indicated in in brackets, were calculated using clustered standard errors (Rogers, 1993). The superscripts *, **, and *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively.

	AR_0	$SE{\cdot}AR_0$	*PBR*	*Mom*	*LS*	*Vol*	*Ret*	*Int.*	R^2(%)
Panel A: Positive Informed Shocks									
$CAR_{1,10}$	−0.149	0.102	−0.006	−0.261	0.007	−3.888	−0.002	0.491	3.08%
	[−2.918 ***]	[3.230 ***]	[−0.774]	[−0.611]	[0.170]	[−5.565 ***]	[−1.521]	[0.685]	
$CAR_{2,10}$	−0.141	0.079	−0.009	−0.249	0.015	−3.104	−0.002	0.372	2.89%
	[−3.149 ***]	[2.911 ***]	[−1.231]	[−0.729]	[0.413]	[−5.302 ***]	[−1.782]	[0.598]	
$CAR_{3,10}$	−0.071	0.060	−0.009	−0.196	0.022	−2.668	−0.002	0.012	2.13%
	[−1.622]	[2.235 **]	[−1.321]	[−0.601]	[0.605]	[−4.684 ***]	[−1.935 *]	[0.020]	
$CAR_{4,10}$	−0.016	0.053	−0.013	0.069	0.041	−2.508	−0.002	−0.536	1.87%
	[−0.280]	[1.964 **]	[−2.068 **]	[0.195]	[1.120]	[−4.545 ***]	[−1.584]	[−0.853]	
$CAR_{5,10}$	0.005	0.056	−0.009	−0.095	0.052	−2.110	−0.002	−0.823	1.67%
	[0.076]	[2.011 **]	[−1.302]	[−0.241]	[1.383]	[−3.806 ***]	[−1.347]	[−1.287]	
$CAR_{6,10}$	−0.025	0.057	−0.007	0.029	0.059	−1.849	−0.002	−0.850	1.48%
	[−0.434]	[2.092 **]	[−0.999]	[0.083]	[1.590]	[−3.245 ***]	[−1.276]	[−1.345]	
$CAR_{7,10}$	−0.017	0.017	−0.009	−0.033	0.061	−0.626	−0.002	−0.834	0.58%
	[−0.271]	[0.724]	[−1.595]	[−0.125]	[1.857 *]	[−1.305]	[−1.511]	[−1.463]	
$CAR_{8,10}$	−0.002	0.016	−0.010	0.001	0.037	−0.039	−0.003	−0.477	0.39%
	[−0.026]	[0.689]	[−1.629]	[0.004]	[1.154]	[−0.083]	[−2.341 **]	[−0.864]	
$CAR_{9,10}$	0.014	0.028	−0.002	0.020	0.057	0.022	−0.001	−0.978	0.40%
	[0.194]	[1.308]	[−0.280]	[0.076]	[1.956 *]	[0.046]	[−0.891]	[−1.887 *]	
Panel B: Negative Informed Shocks									
$CAR_{1,10}$	0.392	−0.053	−0.010	0.326	0.073	−3.690	0.004	0.008	5.49%
	[7.644 ***]	[−2.375 **]	[−2.082 **]	[1.105]	[1.925 *]	[−7.552 ***]	[3.413 ***]	[0.012]	
$CAR_{2,10}$	0.349	−0.043	−0.009	0.187	0.047	−3.029	0.003	0.351	5.10%
	[7.706 ***]	[−2.201 **]	[−2.106 **]	[0.665]	[1.401]	[−7.223 ***]	[2.774 ***]	[0.579]	
$CAR_{3,10}$	0.311	−0.049	−0.006	0.193	0.031	−2.884	0.003	0.491	4.54%
	[7.080 ***]	[−2.574 ***]	[−1.559]	[0.792]	[0.970]	[−7.309 ***]	[2.503 **]	[0.829]	
$CAR_{4,10}$	0.268	−0.038	−0.007	0.234	0.062	−2.636	0.003	−0.139	3.84%
	[6.167 ***]	[−2.010 **]	[−1.557]	[0.945]	[1.903 *]	[−6.169 ***]	[2.626 ***]	[−0.233]	
$CAR_{5,10}$	0.260	−0.037	−0.005	0.316	0.051	−2.569	0.003	0.015	3.51%
	[5.904 ***]	[−1.949 *]	[−0.961]	[1.226]	[1.590]	[−5.977 ***]	[2.277 **]	[0.025]	
$CAR_{6,10}$	0.230	−0.012	−0.003	0.291	0.088	−2.592	0.003	−0.658	3.14%
	[5.264 ***]	[−0.636]	[−0.644]	[1.279]	[2.750 ***]	[−6.109 ***]	[2.536 **]	[−1.106]	
$CAR_{7,10}$	0.115	−0.001	0.000	0.146	0.041	−1.405	0.002	−0.247	0.98%
	[2.775 ***]	[−0.044]	[−0.053]	[0.702]	[1.421]	[−3.890 ***]	[1.804 *]	[−0.467]	
$CAR_{8,10}$	0.071	0.005	−0.003	0.083	0.035	−1.134	0.001	−0.270	0.56%
	[1.682 *]	[0.288]	[−0.755]	[0.369]	[1.200]	[−3.192 ***]	[1.129]	[−0.506]	
$CAR_{9,10}$	0.092	0.005	−0.004	0.084	0.058	−0.764	0.000	−0.529	0.62%
	[2.334 **]	[0.278]	[−1.157]	[0.479]	[1.897 *]	[−2.079 **]	[0.326]	[−1.013]	
Panel C: Positive Uninformed Shocks									
$CAR_{1,10}$	−0.244	0.014	−0.002	−0.842	0.002	−2.979	−0.002	0.857	1.68%
	[−7.894 ***]	[1.058]	[−0.476]	[−3.254 ***]	[0.127]	[−5.222 ***]	[−2.177 **]	[2.540 **]	
$CAR_{2,10}$	−0.187	0.022	−0.001	−0.711	−0.007	−2.568	−0.001	0.806	1.33%
	[−6.722 ***]	[1.843 *]	[−0.236]	[−2.946 ***]	[−0.405]	[−5.029 ***]	[−1.814 *]	[2.625 ***]	
$CAR_{3,10}$	−0.177	0.016	0.000	−0.592	−0.021	−2.462	−0.002	1.037	1.20%
	[−6.843 ***]	[1.396]	[−0.064]	[−2.465 **]	[−1.233]	[−4.801 ***]	[−2.318 **]	[3.402 ***]	
$CAR_{4,10}$	−0.187	0.018	0.000	−0.530	−0.025	−2.630	−0.002	1.176	1.32%
	[−7.437 ***]	[1.506]	[−0.018]	[−2.212 **]	[−1.518]	[−5.149 ***]	[−2.944 ***]	[3.901 ***]	
$CAR_{5,10}$	−0.148	0.006	−0.003	−0.394	−0.019	−2.409	−0.002	0.959	0.98%
	[−5.627 ***]	[0.516]	[−1.100]	[−1.515]	[−1.085]	[−4.619 ***]	[−3.137 ***]	[3.099 ***]	
$CAR_{6,10}$	−0.104	−0.005	−0.005	−0.323	−0.012	−2.568	−0.002	0.746	0.78%
	[−3.838 ***]	[−0.382]	[−1.624]	[−1.232]	[−0.690]	[−4.847 ***]	[−2.944 ***]	[2.326 **]	
$CAR_{7,10}$	−0.061	0.013	−0.002	0.041	−0.014	−1.370	−0.001	0.540	0.24%
	[−2.474 **]	[1.180]	[−0.923]	[0.199]	[−0.870]	[−2.719 ***]	[−1.780 *]	[1.838 *]	
$CAR_{8,10}$	−0.026	0.018	−0.002	0.072	−0.010	−1.416	0.000	0.296	0.16%
	[−0.941]	[1.672 *]	[−0.604]	[0.292]	[−0.588]	[−2.711 ***]	[−0.716]	[0.983]	
$CAR_{9,10}$	−0.017	0.007	−0.001	−0.017	0.000	−1.109	0.000	0.104	0.09%
	[−0.756]	[0.640]	[−0.525]	[−0.086]	[−0.002]	[−2.265 **]	[−0.339]	[0.356]	

Table 2. *Cont.*

	AR_0	$SE{\cdot}AR_0$	PBR	Mom	LS	Vol	Ret	Int.	R^2(%)
				Panel D: Negative Uninformed Shocks					
$CAR_{1,10}$	−0.236 [−3.598 ***]	0.000 [0.013]	−0.001 [−0.145]	0.211 [0.651]	−0.042 [−1.092]	1.861 [1.457]	0.001 [1.234]	−0.404 [−0.556]	1.25%
$CAR_{2,10}$	−0.155 [−2.609 ***]	0.003 [0.157]	−0.001 [−0.210]	0.120 [0.413]	−0.044 [−1.368]	1.788 [1.615]	0.001 [0.976]	−0.017 [−0.027]	0.84%
$CAR_{3,10}$	−0.112 [−1.763 *]	0.002 [0.130]	−0.001 [−0.154]	−0.019 [−0.076]	−0.033 [−1.056]	1.940 [1.747 *]	0.001 [0.972]	−0.038 [−0.061]	0.55%
$CAR_{4,10}$	−0.088 [−1.546]	0.005 [0.281]	−0.001 [−0.147]	0.025 [0.099]	−0.030 [−0.976]	2.059 [1.726 *]	0.001 [0.583]	0.006 [0.011]	0.42%
$CAR_{5,10}$	−0.096 [−1.829 *]	−0.004 [−0.204]	0.000 [−0.074]	0.026 [0.100]	−0.037 [−1.175]	2.396 [2.038 **]	0.001 [0.533]	0.057 [0.097]	0.53%
$CAR_{6,10}$	−0.131 [−2.259 **]	−0.006 [−0.327]	−0.001 [−0.232]	−0.020 [−0.073]	−0.039 [−1.085]	3.034 [2.398 **]	0.001 [0.701]	−0.078 [−0.118]	0.77%
$CAR_{7,10}$	−0.038 [−0.909]	−0.005 [−0.297]	−0.002 [−0.448]	−0.162 [−0.747]	−0.045 [−1.725]	2.677 [2.368 **]	0.001 [0.699]	0.427 [0.949]	0.48%
$CAR_{8,10}$	−0.033 [−0.786]	0.003 [0.155]	0.003 [0.834]	0.009 [0.046]	−0.050 [−1.892 *]	2.659 [2.474 **]	−0.001 [−0.840]	0.597 [1.284]	0.44%
$CAR_{9,10}$	−0.051 [−1.214]	−0.001 [−0.063]	0.006 [1.331]	0.069 [0.330]	−0.045 [−1.735 *]	2.461 [2.398 **]	−0.001 [−0.708]	0.453 [0.999]	0.44%

In the context of positive informed shocks (Panel A), the coefficients (β_1) estimates are significantly negative at the 1% level for post-shock returns $CAR_{k,10}$ with k = 1 and 2. This suggests the presence of a market overreaction to unexpected positive news, as described by De Bondt and Thaler (1985). The effect diminishes as the post-shock observation window extends further from the event day.

In contrast, for negative informed shocks (Panel B), the β_1 estimates are positive across all post-shock returns, and the corresponding t-statistics provide strong evidence indicating a stock price underreaction to the initial shocks. Notably, the observed pattern for informed negative shocks persists over a longer period compared to the pattern observed for informed positive shocks (Panel A), suggesting a slower adjustment of stock prices. This observation aligns with Diamond and Verrecchia's (1987) hypothesis, which proposes that prohibiting short-sale constraints hinder the adjustment of stock prices to bad news.

Furthermore, across all the rows that display significant patterns in post-shock returns in both Panels A and B, the estimates for coefficient β_2 are also significant and exhibit the opposite sign to the estimates for β_1. These findings suggest that the removal of the short sale ban has a substantial effect on mitigating the observed post-shock anomalies, implying a more efficient adjustment of stock prices to the initial shocks. This result is consistent with previous study of Chang et al. (2013), who showed an increase in price efficiency when the short sale ban is removed in the Chinese stock market.

In Panels C and D, the estimated outcomes are associated with uninformed shocks. For both positive and negative shocks, the coefficient (β_1) estimates are negative, indicating the presence of subsequent reversals following these price shocks. However, the statistical significance of these patterns diminishes as the gap (k) between the shock day and the starting day of the post-shock observation window increases.

In the case of uninformed shocks (Panels C and D), the impact of lifting the short sale ban is less pronounced compared to that observed for informed shocks (Panels A and B). Specifically, in the context of positive uninformed shocks (Panel C), only two rows ($CAR_{2,10}$ and $CAR_{8,10}$) show β_2 estimates that are significant at the 10% level. For negative uninformed shocks (Panel D), none of the β_2 estimates achieve statistical significance. This indicates that the removal of the short sale ban has a relatively limited effect on the price adjustment of stocks following uninformed shocks, in contrast to the significant effects noted with informed shocks. These findings suggest that short-selling activities on the event day are likely driven primarily by the informational content of the price shocks.

5.2. The Effects of Short-Sale Activities

Table 3 presents estimation results for Model (2). The *t*-statistics are calculated using the same method as in Model (1). The estimates for the effects of the short-sale intensity (α_1 and α_2) on post-shock returns are the focus of my discussion.

In Panel A, the estimates for β_1 and β_2 reveal a clear pattern of reversals following positive shocks, with the magnitude of these reversals being more pronounced for uninformed shocks ($\beta_1 < 0$, $\beta_2 < 0$). This finding aligns with the research hypothesis that post-shock reversals are indicative of an initial overreaction, particularly in cases where the price shock lacks substantial informational content.

When the level of the short-sale intensity is included as a conditional variable, the estimates for α_1 and α_2 demonstrate a mitigating effect on these reversals. The opposite signs exhibited by α_1 and α_2 relative to β_1 and β_2 suggest that heightened short-sale activity plays a critical role in correcting overreactions. Notably, the reduction in reversal patterns for positive informed shocks implies that short sellers help moderate price inefficiencies by acting as informed arbitragers, a hypothesis central to Diamond and Verrecchia's (1987) framework.

Furthermore, the insignificance of the overreaction effect for positive informed shocks when the short-sale intensity is incorporated underscores the ability of short sellers to accurately interpret and respond to the informational content of shocks. This is a key finding, as it provides empirical support for the hypothesis that short sellers enhance price efficiency by countering overvaluation. Additionally, the significance of α_2 at the 1% level for post-shock returns up to k = 6 underscores the persistence of the moderating impact of short sellers over the adjustment period.

Panel B results highlight a pattern of downward price drifts following negative informed shocks, extending up to k = 6 in post-shock returns. This drift reflects the underreaction hypothesis, where prices take longer to fully incorporate the informational content of bad news. However, when the short-sale intensity is added to the model, the underreaction effect diminishes more quickly compared to the baseline results in Table 1. This observation supports the hypothesis that short sellers facilitate faster price adjustments in response to negative shocks.

The estimates for α_1 reveal that a higher short-sale intensity significantly reduces downward drifts following negative shocks, corroborating the role of short sellers in mitigating inefficiencies driven by underreaction. Importantly, α_2 indicates that the impact of short sales depends on the information content of the price shock. Specifically, short-sale trades are most effective at correcting price inefficiencies when the shocks are informed by bad news, consistent with the hypothesis that short sellers act as informed arbitragers during adverse market conditions.

The test results for α_2, which captures the differential role of the short-sale intensity between informed and uninformed shocks, reveal novel evidence of short sellers' ability to process information associated with price shocks. These findings strongly support the hypothesis that short sellers excel in identifying mispricing and strategically adjusting their trades to correct an over- or underreaction.

This ability is particularly significant in the context of the Chinese stock market, where restrictions on short selling impose additional barriers. The results align with prior studies, such as that by Boehmer and Wu (2013), who observed reduced post-shock drifts following negative earnings surprises with increased short selling, and Chang et al. (2013), who demonstrated improved price efficiency with intensified short-selling activities. The consistency of these findings across markets underscores the robustness of the hypothesis that short sellers play an instrumental role in enhancing price efficiency.

Table 3. Regression analysis of post-shock returns: the impacts of short-sellers' trading activities. Note: This table reports the estimation results for the following regression equation: $CAR_{p,q} = c + \alpha_1 SS_0 + \alpha_2(UN \cdot SS_0) + \beta_1 AR_0 + \beta_2(UN \cdot AR_0) + \gamma' X + u$. $CAR_{p,q}$ is the post-shock abnormal return (%) over the holding period $[t+p, t+q]$. SS_0 represents the level of short-sale intensity and is computed as the percentage of the event day short-sale volume relative to the estimated total volume of lendable shares. AR_0 is the event day abnormal return (%). UN is an indicator variable that indicates uninformed events. Vector X contains a list of controlling variables: price-to-book ratio (*PBR*), momentum (*Mom*), log size (*LS*), trading volume (*Vol*), and the retail investor percentage (*Ret*). Both event day and post-shock abnormal returns are standardized by the corresponding estimation period standard deviations adjusted for forecast errors (see Boehmer et al., 1991; Campbell et al., 1997, pp. 158–163). The *t*-test statistics, indicated in in brackets, were calculated using clustered standard errors (Rogers, 1993). The superscripts *, **, and *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively.

	SS_0	$SS_0 \cdot UN$	AR_0	$AR_0 \cdot UN$	*MOM*	*PBR*	*LS*	*Vol*	*Ret*	*Int*	R^2 (%)
Panel A: Positive Shocks ($AR_0 > 0$)											
$CAR_{1,10}$	−0.017	0.071	−0.017	−0.115	0.004	−0.644	−0.031	−2.919	−0.003	1.037	1.61%
	[−1.211]	[3.732 ***]	[−0.342]	[−5.037 ***]	[0.715]	[−1.369]	[−1.170]	[−2.472 **]	[−1.988 **]	[2.128 **]	
$CAR_{2,10}$	−0.014	0.053	0.000	−0.087	0.004	−0.546	−0.029	−2.716	−0.002	0.840	1.18%
	[−1.237]	[3.271 ***]	[−0.002]	[−4.208 ***]	[0.768]	[−1.317]	[−1.208]	[−2.567 ***]	[−1.139]	[1.902 *]	
$CAR_{3,10}$	−0.006	0.040	−0.020	−0.074	0.003	−0.420	−0.023	−2.295	−0.002	0.761	0.95%
	[−0.525]	[2.438 **]	[−0.477]	[−3.604 ***]	[0.663]	[−0.990]	[−0.977]	[−2.225 **]	[−1.307]	[1.790 *]	
$CAR_{4,10}$	−0.004	0.037	−0.028	−0.070	0.001	−0.431	−0.022	−1.870	−0.003	0.826	1.00%
	[−0.318]	[2.270 **]	[−0.659]	[−3.410 ***]	[0.223]	[−1.022]	[−0.973]	[−1.849 *]	[−2.465 **]	[2.014 **]	
$CAR_{5,10}$	−0.003	0.032	−0.028	−0.069	−0.001	−0.373	−0.006	−1.498	−0.003	0.516	0.83%
	[−0.294]	[2.082 **]	[−0.627]	[−3.406 ***]	[−0.221]	[−0.846]	[−0.259]	[−1.514]	[−2.007**]	[1.304]	
$CAR_{6,10}$	−0.003	0.030	−0.023	−0.068	−0.005	−0.350	0.014	−1.426	−0.003	0.184	0.82%
	[−0.273]	[1.982 **]	[−0.536]	[−3.388 ***]	[−0.803]	[−0.803]	[0.646]	[−1.387]	[−2.017 **]	[0.464]	
$CAR_{7,10}$	0.003	0.019	0.005	−0.022	−0.002	−0.072	0.029	−0.114	−0.001	−0.414	0.22%
	[0.335]	[1.365]	[0.137]	[−1.269]	[−0.362]	[−0.202]	[1.463]	[−0.116]	[−0.482]	[−1.144]	
$CAR_{8,10}$	0.010	0.013	0.018	−0.008	−0.006	0.114	0.029	0.218	0.000	−0.526	0.25%
	[1.032]	[0.884]	[0.470]	[−0.457]	[−1.110]	[0.344]	[1.527]	[0.241]	[−0.180]	[−1.487]	
$CAR_{9,10}$	0.009	−0.001	0.022	−0.022	−0.005	−0.168	0.034	0.326	0.000	−0.558	0.18%
	[0.875]	[−0.083]	[0.630]	[−1.330]	[−0.973]	[−0.505]	[1.573]	[0.380]	[−0.204]	[−1.448]	
Panel B: Negative Shocks ($AR_0 < 0$)											
$CAR_{1,10}$	0.082	−0.084	0.199	−0.021	0.002	−0.137	−0.045	−3.695	0.003	1.368	2.80%
	[2.645 ***]	[−2.309 **]	[3.570 ***]	[−1.055]	[0.198]	[−0.543]	[−0.974]	[−3.441 ***]	[2.180 **]	[1.580]	
$CAR_{2,10}$	0.067	−0.064	0.203	−0.012	−0.001	−0.207	−0.033	−3.042	0.003	1.192	2.84%
	[2.456 **]	[−2.033**]	[3.943 ***]	[−0.684]	[−0.132]	[−0.916]	[−0.864]	[−3.295 ***]	[2.502 **]	[1.645 *]	
$CAR_{3,10}$	0.055	−0.053	0.165	−0.002	−0.002	−0.219	−0.038	−2.838	0.003	1.168	2.19%
	[2.191 **]	[−1.807*]	[3.460 ***]	[−0.143]	[−0.233]	[−0.941]	[−1.079]	[−2.945 ***]	[2.532 **]	[1.768 *]	

Table 3. *Cont.*

	SS_0	$SS_0 \cdot UN$	AR_0	$AR_0 \cdot UN$	*MOM*	*PBR*	*LS*	*Vol*	*Ret*	*Int*	R^2 (%)
					Panel B: Negative Shocks ($AR_0 < 0$)						
$CAR_{4,10}$	0.053 [2.504 **]	−0.043 [−1.688 *]	0.133 [2.552 **]	0.014 [0.821]	−0.002 [−0.183]	−0.108 [−0.470]	−0.022 [−0.613]	−2.506 [−2.517**]	0.003 [2.421 **]	0.797 [1.196]	1.79%
$CAR_{5,10}$	0.053 [2.930 ***]	−0.043 [−1.920 *]	0.112 [2.311 **]	0.011 [0.654]	0.002 [0.242]	−0.141 [−0.620]	−0.041 [−1.074]	−2.133 [−2.229 **]	0.003 [1.835 *]	1.043 [1.465]	1.58%
$CAR_{6,10}$	0.048 [2.824 ***]	−0.048 [−2.253 **]	0.106 [2.033 **]	0.002 [0.098]	0.002 [0.233]	−0.188 [−0.720]	−0.040 [−0.895]	−1.538 [−1.489]	0.002 [1.515]	0.983 [1.183]	1.12%
$CAR_{7,10}$	0.024 [1.936 *]	−0.017 [−1.067]	0.073 [1.309]	0.009 [0.557]	−0.001 [−0.190]	−0.266 [−1.168]	−0.027 [−0.862]	−0.020 [−0.020]	0.001 [1.025]	0.684 [1.145]	0.57%
$CAR_{8,10}$	0.020 [1.554]	−0.015 [−0.915]	0.063 [1.229]	0.014 [0.899]	0.002 [0.294]	−0.239 [−1.174]	−0.034 [−1.002]	0.489 [0.511]	0.000 [0.053]	0.785 [1.268]	0.49%
$CAR_{9,10}$	0.012 [1.197]	−0.012 [−0.911]	0.046 [0.748]	0.009 [0.542]	0.001 [0.170]	−0.196 [−1.063]	−0.021 [−0.641]	0.876 [0.990]	0.000 [−0.047]	0.513 [0.849]	0.29%

Overall, the results underscore the critical role of short sellers in addressing price inefficiencies following significant price shocks. By showing that short-selling activity reduces post-shock reversals and drifts, the findings offer compelling empirical evidence of short sellers' contribution to market efficiency. Their ability to act as informed arbitragers, effectively interpreting and responding to the informational content of price shocks, aligns with the theoretical framework of Diamond and Verrecchia (1987). An important implication of this conclusion is that easing short-sale constraints—such as lowering borrowing costs and expanding lending programs—could promote more efficient price adjustments. Ultimately, these findings emphasize the significance of short selling in enhancing market stability and provide valuable insights for regulators in markets where short selling remains heavily restricted.

5.3. Short Sellers' Responses to Extreme Price Moves

The findings presented in the preceding sections have demonstrated that short sellers possess the capability to discern the information content embedded within unexpected price shocks. In order to establish the connection between the trading actions of short sellers and the mitigation of post-shock anomalies, it is essential to comprehend the role played by short sellers during these price shocks.

Table 4 displays the concurrent correlation between the degrees of short-sale intensity and the magnitude of event day abnormal returns ($|AR_0|$). The statistical significance of the results was evaluated using Spearman's rank correlation test, a non-parametric method that measures the strength and direction of association between two ranked variables. Additionally, Pearson's correlation coefficient was calculated to assess the linear relationship between the short-sale intensity and price shock magnitude. Only price events with a non-zero short-selling volume are taken into account in the computation.[14]

Table 4. Correlation between the magnitude of the price shock and short-sale intensity Note: This table provides the statistics of contemporary correlation between the short-sale intensity and the magnitude of the abnormal price changes on the shock day. Spearman's rank correlation test was used to evaluate the statistical significance (*p*-value). The short-sale intensity (SS_0) is calculated as the percentage of the event day short-sale volume relative to the estimated total volume of lendable shares. A price event is considered informed (uninformed) if it is (not) accompanied by relevant news released on the same or adjacent days.

	Informed Positive	**Informed Negative**	**Uninformed Positive**	**Uninformed Negative**
Mean SS_0 (%)	1.8543	1.3408	1.0285	1.0373
Pearson's r	0.1495	0.0486	0.1242	−0.0778
Spearman's rho	0.1519	0.1748	0.1667	0.007
p-value (rho)	0	0	0	0.7339

The correlation analysis indicates that the short-sale intensity rises along with the magnitude of informed price shocks and uninformed positive shocks. In these instances, the Spearman correlation coefficients are significant at the 1% level. However, in the case of uninformed negative shocks, where short positions do not align with the arbitrage strategy, the correlation between the short-sale intensity and the magnitude of the price shock is both minimal and statistically insignificant. These findings collectively suggest that short sellers are drawn to arbitrage opportunities where they trade against overvaluation. Boehmer and Wu (2013) also look at the contemptuous correlation between the magnitude of price shocks and short-sale activities. They find short sellers (from NYSE) tend to reduce their trades on price shock days. However, their analysis focuses on negative price shocks followed by reversals, which are related to the uninformed price shocks in this study.

5.4. Stock Portfolios with Different Levels of Short Intensity

Recent studies focusing on short-selling activities in the Chinese stock market have highlighted the role of short sellers as informed traders (Feng & Chan, 2016; Wan, 2020). This study builds on that premise, providing evidence that the short-selling intensity is linked to the correction of price inefficiencies. The observed decrease in post-shock anomalies among shortable stocks with heightened short-selling activities suggests that short sellers actively target overpriced stocks, contributing to improved market efficiency. This aligns with the research objective of understanding how short sellers influence post-shock stock returns. One implication of these findings is that stocks experiencing a high short-selling intensity are more likely to be overpriced compared to those with lower short-selling intensity.

To further investigate this relationship, I constructed portfolios based on the short-selling intensity. Starting on 2 May 2016, and following each weekend holiday, shortable stocks were ranked by their scaled volume of short interest, as reported by the Chinese stock exchanges. The top and bottom 25 percentiles were used to form high short interest (HS) and low short interest (LS) portfolios, respectively. Non-shortable stocks were grouped into a separate non-shortable (NS) portfolio. The daily returns for these portfolios were calculated using equal-weighted averages to ensure comparability across stocks within each portfolio.

To assess whether the observed return patterns align with the study's objective of linking short-selling activity to price efficiency, I employed the Fama–French three-factor model (Fama & French, 1993). This model decomposes portfolio returns into components attributed to market risk (MRK), size (SMB), and value (HML) factors, with the alpha term (α) capturing any unexplained excess returns. Using this framework allows us to examine whether high levels of short interest result in significant deviations from expected returns, consistent with the hypothesis that short sellers target mispriced stocks.

The results presented in Table 5 provide strong evidence supporting the hypothesis that the short-selling intensity is a key factor in correcting price inefficiencies. The high short (HS) portfolio exhibits a statistically significant negative daily alpha at the 1% level, indicating an underperformance of approximately 0.06% compared to both the low short (LS) and non-shortable (NS) portfolios. This underperformance supports the conclusion that heavily shorted stocks tend to be more overpriced and experience downward price adjustments over time, consistent with previous findings in other markets (Desai et al., 2002; Boehmer et al., 2008).

In contrast, the daily alpha for the non-shortable (NS) portfolio is not statistically significant. This suggests that non-shortable stocks may remain overvalued, with any uncertainties in their returns already reflected in the market pricing. The use of the Fama–French model in this context reinforces the study's objective of isolating the effects of the short-selling intensity from broader market influences, providing a robust framework to link short seller activity to market efficiency.

Table 5. Fama–French regressions: low vs. high short intensity portfolios. Note: This table presents the results from Fama–French calendar time regressions of excess daily returns of different portfolios. The data span from 2 May 2016 to 30 April 2023. On the first trading days following the weekend holiday, the sample stocks are sorted based on the volume of short interest, scaled by the volume of lendable shares, as reported by the Chinese stock exchanges. The top and bottom 25 percentiles are used to construct the portfolios of high short interest (HS) and low short interest (LS) stocks, as indicated in the table. Additionally, the non-shortable stocks are grouped together to form the non-shortable (NS) portfolio. The portfolio returns are calculated by assigning equal weights to each component stock. The market excess return (MRK), SMB, and HML are three factors from the study by Fama and French (1993). Robust t-statistics are provided in brackets.

Portfolios	*Alpha*	*MRK*	*SMB*	*HML*	*R^2 (%)*
LS	0.014	1.022	0.836	0.204	91.96%
	[1.600]	[110.831]	[31.050]	[10.022]	
HS	−0.048	1.210	0.798	0.190	86.78%
	[−3.457]	[79.733]	[21.551]	[5.833]	
NS	0.015	1.056	1.343	−0.191	94.83%
	[1.933]	[137.468]	[58.036]	[−10.645]	

6. Robustness

The estimation results for Models (1) and (2) are based on standardized abnormal returns, which are calculated by dividing the difference between daily returns and expected returns based on the Fama and French three-factor model (Fama & French, 1993) by the corresponding estimation period standard deviations adjusted for forecast errors (see Boehmer et al., 1991; Campbell et al., 1997, pp. 158–163). However, my conclusions remain unchanged when non-standardized abnormal returns are used for the estimation of Equations (1) and (2). The corresponding results are presented in Tables A1 and A2 in Appendix A.

The selection of price events for estimating Model (1) includes stocks that remain non-shortable even after the implementation of the pilot program. These persistently non-shortable stocks might display distinct post-shock return behaviors compared to their shortable counterparts. For instance, the pilot program often excludes illiquid small-cap stocks. As a result, β_2 in Model (1) could reflect differences in return patterns between shortable and persistently non-shortable stocks. To address this issue, I re-estimated Model (1) using only price events from shortable stocks.[15] The resultant estimation findings, showcased in Table A3 of Appendix A, affirm my previous conclusions, thereby ruling out the alternative explanation.

7. Conclusions

This paper investigates the roles of short-sale constraints and short-sale activities in shaping the behavior of stock returns following large price shocks. Using a modified version of Savor's (2012) regression model, I introduce an indicator for shortable stocks and a measure of short-sale intensity concurrent with price shocks. The results demonstrate that increased short-sale activity is associated with a reduction in post-shock anomalies, particularly when the price shocks are news-driven. This finding supports Diamond and Verrecchia's (1997) hypothesis, providing empirical evidence that short sellers play a critical role in enhancing price efficiency by mitigating both overreaction and underreaction in stock prices. Furthermore, the analysis highlights that short sellers act as informed arbitragers, strategically targeting overvaluation during price shocks. These conclusions remain robust across various controls, post-shock horizons, and abnormal return models, reinforcing their validity.

The findings directly address the study's research questions by clarifying the mechanisms through which short sellers influence post-shock stock price behavior and market efficiency. First, the results reconcile inconsistencies in prior empirical research by demonstrating the pivotal role of short sales in reducing post-shock anomalies, an area often overlooked in markets with stringent short-sale constraints. Second, the study provides new insights into the behavior of short sellers in mainland China, showing that their actions, publicly disclosed through daily exchange reports, contribute significantly to correcting overvaluation. These findings emphasize the informational value of short sellers' activities to other market participants and their strategic importance in the market.

The implications of this study are particularly relevant for regulators and policymakers. The evidence suggests that excessive short-sale constraints, such as high borrowing costs and limited share availability, may impede market efficiency by limiting the corrective actions of short sellers. To address these issues, regulators could expand share-lending programs, reduce borrowing costs, and introduce reforms to foster a more efficient short-selling environment. Additionally, enabling broader participation in short selling could improve liquidity and provide more opportunities for informed arbitrage, further supporting price efficiency. These measures would not only benefit market participants but also support regulators in promoting more stable and transparent financial markets.

In conclusion, this study provides robust empirical evidence on the roles of short sellers in mitigating post-shock anomalies and enhancing price efficiency. By addressing the research questions with a focus on the unique context of the Chinese stock market, the findings contribute to resolving key gaps in the literature and offer practical recommendations for improving market operations. The study highlights the need for carefully balanced regulatory reforms that allow short selling to fulfill its potential in fostering fairness, efficiency, and stability in financial markets.

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Appendix A

Table A1. Regression analysis of post-shock returns: the impact of removing short sale bans (a robustness check). Note: This table reports the estimation results for the following regression equation: $CAR_{p,q} = c + \beta_1 AR_0 + \beta_2 (SE \cdot AR_0) + \gamma' X + u$. $CAR_{p,q}$ is the post-shock abnormal return (%) over the holding period [$t+p$, $t+q$]. AR_0 is the event day abnormal return (%). The dummy variable SE indicates shortable price events. Vector X contains a list of controlling variables: momentum (*Mom*), price-to-book ratio (*PBR*), log size (*LS*), event day scaled trading volume (*Vol*), and the retail investor percentage (*Ret*). The t-test statistics, indicated in in brackets, were calculated using clustered standard errors (Rogers, 1993). The superscripts *, **, and *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively.

	AR_0	$SE \cdot AR_0$	PBR	Mom	LS	Vol	Ret	Int.	R^2 (%)
				Panel A: Positive Informed Shocks					
$CAR_{1,10}$	−0.531 [−4.178 ***]	0.137 [1.733 *]	−0.066 [−1.234]	−0.293 [−1.125]	0.391 [1.652 *]	−24.742 [−5.580 ***]	−0.009 [−1.118]	−1.663 [−0.414]	3.26%
$CAR_{2,10}$	−0.407 [−4.011 ***]	0.100 [1.607]	−0.074 [−1.708 *]	−0.246 [−1.194]	0.356 [1.873 *]	−18.476 [−5.179 ***]	−0.009 [−1.385]	−1.921 [−0.590]	2.99%
$CAR_{3,10}$	−0.447 [−4.597 ***]	0.078 [1.320]	−0.069 [−1.768 *]	−0.187 [−0.983]	0.305 [1.709 *]	−14.628 [−4.522 ***]	−0.008 [−1.414]	−0.943 [−0.310]	2.61%
$CAR_{4,10}$	−0.422 [−4.726 ***]	0.055 [1.036]	−0.090 [−2.577 ***]	−0.037 [−0.203]	0.395 [2.383 **]	−12.290 [−4.252 ***]	−0.007 [−1.304]	−2.797 [−0.990]	2.44%

Table A1. *Cont.*

	AR_0	$SE{\cdot}AR_0$	*PBR*	*Mom*	*LS*	*Vol*	*Ret*	*Int.*	R^2 (%)
Panel A: Positive Informed Shocks									
$CAR_{5,10}$	−0.350	0.049	−0.068	−0.043	0.405	−9.872	−0.008	−3.585	2.12%
	[−4.089 ***]	[0.977]	[−1.965**]	[−0.245]	[2.599 ***]	[−3.685 ***]	[−1.410]	[−1.364]	
$CAR_{6,10}$	−0.224	0.035	−0.052	0.047	0.412	−7.865	−0.007	−4.689	1.59%
	[−2.857 ***]	[0.728]	[−1.700*]	[0.299]	[2.848 ***]	[−3.089 ***]	[−1.431]	[−1.956 **]	
$CAR_{7,10}$	−0.065	0.012	−0.055	0.057	0.328	−1.825	−0.008	−4.384	0.75%
	[−1.129]	[0.327]	[−2.318 **]	[0.520]	[2.950 ***]	[−0.925]	[−1.811 *]	[−2.361 **]	
$CAR_{8,10}$	−0.077	0.014	−0.051	0.090	0.204	0.286	−0.008	−2.377	0.57%
	[−1.620]	[0.445]	[−2.292 **]	[0.992]	[2.179 **]	[0.171]	[−2.256 **]	[−1.527]	
$CAR_{9,10}$	−0.022	0.025	−0.016	0.057	0.191	0.456	−0.002	−2.944	0.41%
	[−0.588]	[1.025]	[−0.754]	[0.765]	[2.616 ***]	[0.324]	[−0.866]	[−2.402 **]	
Panel B: Negative Informed Shocks									
$CAR_{1,10}$	0.542	−0.139	−0.040	−0.024	0.203	−23.992	0.040	−1.635	3.76%
	[4.402 ***]	[−2.161**]	[−1.183]	[−0.200]	[0.957]	[−7.757 ***]	[4.888 ***]	[−0.438]	
$CAR_{2,10}$	0.355	−0.107	−0.031	−0.095	0.072	−18.937	0.028	−0.085	3.24%
	[3.424 ***]	[−2.033 **]	[−1.197]	[−0.922]	[0.410]	[−7.665 ***]	[4.039 ***]	[−0.028]	
$CAR_{3,10}$	0.281	−0.112	−0.024	−0.057	−0.013	−16.767	0.024	0.957	2.82%
	[3.087 ***]	[−2.322**]	[−0.952]	[−0.634]	[−0.083]	[−7.327 ***]	[3.875 ***]	[0.340]	
$CAR_{4,10}$	0.246	−0.067	−0.028	−0.037	0.132	−14.159	0.023	−1.457	2.41%
	[2.910 ***]	[−1.521]	[−1.091]	[−0.438]	[0.894]	[−6.398 ***]	[4.044 ***]	[−0.562]	
$CAR_{5,10}$	0.200	−0.034	−0.018	0.015	0.138	−12.613	0.019	−1.725	1.93%
	[2.544**]	[−0.830]	[−0.742]	[0.178]	[0.994]	[−5.991 ***]	[3.558 ***]	[−0.711]	
$CAR_{6,10}$	0.122	−0.022	−0.007	−0.009	0.228	−11.501	0.021	−3.773	1.84%
	[1.713 *]	[−0.556]	[−0.325]	[−0.118]	[1.808]	[−5.782 ***]	[4.073 ***]	[−1.728]	
$CAR_{7,10}$	0.099	0.014	0.004	−0.041	0.047	−5.674	0.011	−0.265	0.69%
	[1.737 *]	[0.487]	[0.231]	[−0.669]	[0.478]	[−3.743 ***]	[2.694 ***]	[−0.156]	
$CAR_{8,10}$	0.064	−0.009	−0.005	−0.029	−0.007	−3.890	0.007	0.444	0.45%
	[1.270]	[−0.343]	[−0.314]	[−0.526]	[−0.081]	[−3.030 ***]	[1.983 **]	[0.301]	
$CAR_{9,10}$	0.031	0.001	−0.006	−0.002	0.077	−2.229	0.003	−1.037	0.25%
	[0.743]	[0.038]	[−0.539]	[−0.046]	[1.053]	[−1.994 ***]	[1.056]	[−0.814]	
Panel C: Positive Uninformed Shocks									
$CAR_{1,10}$	−0.302	0.107	−0.002	−0.365	−0.101	−19.122	−0.005	3.301	1.13%
	[−4.818 ***]	[2.822 ***]	[−0.092]	[−2.026 **]	[−1.021]	[−4.832 ***]	[−1.216]	[1.910 *]	
$CAR_{2,10}$	−0.187	0.089	−0.002	−0.326	−0.064	−16.318	−0.004	2.190	0.99%
	[−3.582 ***]	[2.777 ***]	[−0.108]	[−2.043 **]	[−0.771]	[−4.882 ***]	[−1.137]	[1.509]	
$CAR_{3,10}$	−0.156	0.070	0.000	−0.207	−0.132	−15.330	−0.006	3.320	0.85%
	[−3.262 ***]	[2.307 **]	[0.015]	[−1.405]	[−1.741]	[−4.850 ***]	[−1.642]	[2.458 **]	
$CAR_{4,10}$	−0.148	0.073	0.002	−0.151	−0.159	−15.285	−0.008	3.825	0.94%
	[−3.234 ***]	[2.540 **]	[0.133]	[−1.074]	[−2.226 **]	[−5.292 ***]	[−2.361 **]	[2.979 ***]	
$CAR_{5,10}$	−0.141	0.049	−0.012	−0.051	−0.140	−12.984	−0.007	3.549	0.80%
	[−3.264 ***]	[1.808 *]	[−0.888]	[−0.373]	[−2.083 **]	[−4.706 ***]	[−2.481 **]	[2.926 ***]	
$CAR_{6,10}$	−0.076	0.039	−0.015	−0.048	−0.113	−11.303	−0.006	3.038	0.74%
	[−2.331 **]	[1.571]	[−1.250]	[−0.388]	[−1.794 *]	[−4.518 ***]	[−2.298 **]	[2.703 ***]	
$CAR_{7,10}$	0.012	0.017	−0.004	−0.005	−0.069	−7.048	−0.004	1.403	0.26%
	[0.406]	[0.866]	[−0.444]	[−0.061]	[−1.386]	[−3.253 ***]	[−1.817 *]	[1.569]	
$CAR_{8,10}$	−0.003	0.029	−0.003	0.067	−0.058	−6.013	−0.001	1.101	0.21%
	[−0.096]	[1.687]	[−0.318]	[0.886]	[−1.365]	[−3.176 ***]	[−0.533]	[1.452]	
$CAR_{9,10}$	−0.006	0.002	−0.001	0.048	−0.008	−3.721	−0.001	0.308	0.12%
	[−0.280]	[0.110]	[−0.158]	[0.757]	[−0.225]	[−2.355 **]	[−0.490]	[0.490]	
Panel D: Negative Uninformed Shocks									
$CAR_{1,10}$	−0.200	−0.036	−0.059	−0.034	0.025	16.058	0.004	−2.539	0.51%
	[−2.319 **]	[−0.694]	[−1.770 *]	[−0.190]	[0.149]	[2.055 **]	[0.714]	[−0.871]	
$CAR_{2,10}$	−0.141	−0.030	−0.047	−0.048	−0.038	14.193	0.004	−0.962	0.48%
	[−1.945 *]	[−0.680]	[−1.717 *]	[−0.326]	[−0.275]	[2.223 **]	[0.720]	[−0.403]	
$CAR_{3,10}$	−0.106	−0.037	−0.039	−0.076	−0.021	13.778	0.003	−0.886	0.44%
	[−1.563]	[−0.900]	[−1.526]	[−0.576]	[−0.168]	[2.258 **]	[0.557]	[−0.394]	
$CAR_{4,10}$	−0.072	−0.033	−0.031	−0.049	−0.008	13.672	0.000	−0.877	0.40%
	[−1.151]	[−0.859]	[−1.374]	[−0.405]	[−0.066]	[2.255 **]	[0.068]	[−0.419]	
$CAR_{5,10}$	−0.058	−0.036	−0.030	−0.062	−0.006	13.502	−0.001	−0.837	0.43%
	[−0.977]	[−0.986]	[−1.443]	[−0.528]	[−0.051]	[2.456 **]	[−0.190]	[−0.418]	
$CAR_{6,10}$	−0.060	−0.032	−0.038	−0.065	0.020	15.056	0.000	−1.293	0.57%
	[−1.053]	[−0.940]	[−1.747]	[−0.557]	[0.176]	[2.805 ***]	[−0.036]	[−0.658]	
$CAR_{7,10}$	−0.033	−0.022	−0.025	−0.063	−0.052	11.584	0.001	0.243	0.48%
	[−0.738]	[−0.836]	[−1.552]	[−0.796]	[−0.666]	[2.497 **]	[0.261]	[0.184]	
$CAR_{8,10}$	−0.053	0.003	−0.001	−0.006	−0.072	9.990	−0.003	0.614	0.50%
	[−1.403]	[0.118]	[−0.049]	[−0.091]	[−1.050]	[2.572 ***]	[−1.251]	[0.532]	
$CAR_{9,10}$	−0.042	0.002	0.005	0.015	−0.048	7.219	−0.002	0.375	0.43%
	[−1.366]	[0.090]	[0.421]	[0.268]	[−0.853]	[2.400 **]	[−1.177]	[0.400]	

Table A2. Regression analysis of post-shock returns: the impacts of short sellers' trading activities (a robustness check). Note: This table reports the estimation results for the following regression equation: $CAR_{p,q} = c + \alpha_1 SS_0 + \alpha_2 (UN \cdot SS_0) + \beta_1 AR_0 + \beta_2 (UN \cdot AR_0) + \gamma' X + u$. $CAR_{p,q}$ is the post-shock abnormal return (%) over the holding period [$t + p$, $t + q$]. SS_0 represents the level of short-sale intensity and is computed as the percentage of the event day short-sale volume relative to the estimated total volume of lendable shares. AR_0 is the event day abnormal return (%). UN is a binary variable that indicates uninformed events. Vector X contains a list of controlling variables: price-to-book ratio (*PBR*), momentum (*Mom*), log size (*LS*), trading volume (*Vol*), and the retail investor percentage (*Ret*). The *t*-test statistics, indicated in in brackets, were calculated using clustered standard errors (Rogers, 1993). The superscripts *, **, and *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively.

	SS_0	$SS_0 \cdot UN$	AR_0	$AR_0 \cdot UN$	*MOM*	*PBR*	*LS*	*Vol*	*Ret*	*Int*	R^2 (%)
					Panel A: Positive Shocks ($AR_0 > 0$)						
$CAR_{1,10}$	−0.112	0.406	0.118	−0.203	0.028	−0.281	−0.211	−20.897	−0.011	4.266	1.16%
	[−1.674 *]	[3.950 ***]	[1.050]	[−3.303 ***]	[0.761]	[−0.908]	[−1.554]	[−2.803 ***]	[−1.239]	[1.592]	
$CAR_{2,10}$	−0.088	0.287	0.096	−0.151	0.018	−0.219	−0.146	−19.271	−0.003	3.050	0.99%
	[−1.647 *]	[3.384 ***]	[1.025]	[−2.970 ***]	[0.573]	[−0.850]	[−1.280]	[−3.111 ***]	[−0.430]	[1.344]	
$CAR_{3,10}$	−0.037	0.202	0.047	−0.108	0.010	−0.088	−0.107	−15.648	−0.004	2.403	0.72%
	[−0.731]	[2.475 **]	[0.541]	[−2.213 **]	[0.354]	[−0.362]	[−1.022]	[−2.732 ***]	[−0.600]	[1.150]	
$CAR_{4,10}$	−0.024	0.170	0.014	−0.074	−0.003	−0.056	−0.091	−11.661	−0.011	2.380	0.66%
	[−0.475]	[2.284 **]	[0.181]	[−1.632]	[−0.101]	[−0.242]	[−0.948]	[−2.217 **]	[−1.680]	[1.231]	
$CAR_{5,10}$	−0.018	0.144	−0.026	−0.073	−0.005	0.020	−0.049	−8.903	−0.007	1.706	0.52%
	[−0.420]	[2.150 **]	[−0.362]	[−1.777 *]	[−0.194]	[0.095]	[−0.549]	[−1.829 *]	[−1.241]	[0.957]	
$CAR_{6,10}$	−0.022	0.127	−0.011	−0.072	−0.017	−0.051	0.014	−6.934	−0.008	0.610	0.51%
	[−0.546]	[2.091 **]	[−0.166]	[−1.878 *]	[−0.604]	[−0.249]	[0.177]	[−1.478]	[−1.346]	[0.377]	
$CAR_{7,10}$	0.014	0.000	0.052	−0.030	−0.005	0.043	0.068	−3.203	−0.001	−1.221	0.11%
	[0.425]	[0.006]	[1.087]	[−1.047]	[−0.265]	[0.295]	[1.088]	[−0.804]	[−0.164]	[−0.990]	
$CAR_{8,10}$	0.028	−0.015	0.003	−0.003	−0.018	0.091	0.045	−0.415	0.001	−0.740	0.07%
	[0.954]	[−0.321]	[0.083]	[−0.118]	[−0.997]	[0.769]	[0.846]	[−0.127]	[0.149]	[−0.701]	
$CAR_{9,10}$	0.021	0.010	−0.020	−0.032	−0.005	0.013	0.065	0.654	0.000	−0.823	0.19%
	[0.803]	[0.264]	[−0.639]	[−1.657 *]	[−0.400]	[0.129]	[1.402]	[0.259]	[0.102]	[−0.922]	
					Panel B: Negative Shocks ($AR_0 < 0$)						
$CAR_{1,10}$	0.424	−0.347	0.377	−0.188	0.047	−0.166	−0.166	−13.966	0.031	3.507	2.20%
	[2.511 **]	[−1.812 *]	[2.710 ***]	[−3.154 ***]	[0.724]	[−0.857]	[−0.756]	[−1.906 *]	[3.331 ***]	[0.827]	
$CAR_{2,10}$	0.321	−0.234	0.255	−0.142	0.016	−0.192	−0.121	−11.361	0.029	2.241	1.99%
	[2.386 **]	[−1.526]	[2.157 **]	[−2.831 ***]	[0.299]	[−1.152]	[−0.677]	[−1.892 *]	[3.706 ***]	[0.639]	
$CAR_{3,10}$	0.249	−0.179	0.182	−0.126	0.004	−0.182	−0.141	−8.607	0.026	2.285	1.52%
	[2.228 **]	[−1.375]	[1.729 *]	[−2.787 ***]	[0.089]	[−1.162]	[−0.887]	[−1.467]	[3.577 ***]	[0.729]	
$CAR_{4,10}$	0.213	−0.127	0.155	−0.095	0.003	−0.105	−0.067	−6.412	0.021	1.039	1.17%
	[2.298 **]	[−1.165]	[1.597]	[−2.191 **]	[0.072]	[−0.681]	[−0.457]	[−1.148]	[3.101 ***]	[0.361]	
$CAR_{5,10}$	0.209	−0.134	0.245	−0.101	0.008	−0.115	−0.129	−3.950	0.015	2.820	1.30%
	[2.483 **]	[−1.381]	[2.769 ***]	[−2.487 **]	[0.190]	[−0.777]	[−0.910]	[−0.793]	[2.441 **]	[1.018]	
$CAR_{6,10}$	0.173	−0.131	0.176	−0.099	0.001	−0.145	−0.067	−0.382	0.014	1.326	0.95%
	[2.404 **]	[−1.550]	[1.991 **]	[−2.535 **]	[0.036]	[−1.013]	[−0.476]	[−0.080]	[2.288 **]	[0.487]	
$CAR_{7,10}$	0.070	−0.026	0.091	−0.059	−0.018	−0.155	−0.019	2.989	0.008	0.329	0.52%
	[1.786 *]	[−0.488]	[1.292]	[−2.097 **]	[−0.558]	[−1.612]	[−0.189]	[0.676]	[1.622]	[0.169]	
$CAR_{8,10}$	0.044	−0.006	0.007	−0.020	0.008	−0.135	−0.047	4.428	0.002	0.476	0.37%
	[0.994]	[−0.109]	[0.129]	[−0.813]	[0.320]	[−1.484]	[−0.521]	[1.183]	[0.454]	[0.275]	
$CAR_{9,10}$	0.018	−0.001	0.036	−0.016	0.010	−0.095	−0.047	4.047	0.000	0.868	0.25%
	[0.667]	[−0.038]	[0.785]	[−0.771]	[0.372]	[−1.366]	[−0.659]	[1.434]	[−0.088]	[0.639]	

Table A3. Regression analysis of post-shock returns: the impact of removing short sale bans (a robustness check with shortable stocks only). Note: This table reports the estimation results for the following regression equation: $CAR_{p,q} = c + \beta_1 AR_0 + \beta_2 (SE \cdot AR_0) + \gamma' X + u$. $CAR_{p,q}$ is the post-shock abnormal return (%) over the holding period [$t + p$, $t + q$]. AR_0 is the event day abnormal return (%). The dummy variable *SE* indicates shortable price events. Vector *X* contains a list of controlling variables: momentum (*Mom*), price-to-book ratio (*PBR*), log size (*LS*), event-day scaled trading volume (*Vol*), and the retail investor percentage (*Ret*). Both event day and post-shock abnormal returns are standardized by the corresponding estimation period standard deviations adjusted for forecast errors (see Boehmer et al., 1991; Campbell et al., 1997, pp. 158–163). The *t*-test statistics, indicated in in brackets, were calculated using clustered standard errors (Rogers, 1993). The superscripts *, **, and *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively.

	AR_0	$SE \cdot AR_0$	*Mom*	*PBR*	*LS*	*Vol*	*Ret*	*Int.*	R^2 (%)
Panel A: Positive Informed Shocks									
$CAR_{1,10}$	−0.152	0.122	0.021	−0.204	−0.139	−2.918	−0.005	2.951	2.13%
	[−2.146 **]	[3.460 **]	[1.592]	[−0.415]	[−2.468 **]	[−2.439 **]	[−2.308 **]	[3.047 ***]	
$CAR_{2,10}$	−0.170	0.097	0.016	−0.344	−0.116	−2.333	−0.005	2.683	2.12%
	[−2.965 ***]	[3.257 **]	[1.359]	[−0.817]	[−2.363 **]	[−2.336 **]	[−2.304 **]	[3.161 ***]	
$CAR_{3,10}$	−0.111	0.074	0.009	−0.221	−0.076	−1.888	−0.004	1.781	1.34%
	[−1.883 *]	[2.523 **]	[0.787]	[−0.474]	[−1.564]	[−1.921 *]	[−1.973 **]	[2.129 **]	
$CAR_{4,10}$	−0.066	0.065	0.004	0.325	−0.051	−2.173	−0.003	1.155	1.09%
	[−0.925]	[2.159 **]	[0.306]	[0.675]	[−1.029]	[−2.251 **]	[−1.466]	[1.342]	
$CAR_{5,10}$	−0.057	0.071	0.013	0.198	−0.041	−1.773	−0.002	0.860	0.92%
	[−0.712]	[2.282 **]	[1.135]	[0.380]	[−0.845]	[−1.848 *]	[−1.001]	[1.009]	
$CAR_{6,10}$	−0.064	0.069	0.010	0.244	−0.052	−1.639	−0.003	1.165	1.01%
	[−0.870]	[2.273 **]	[0.839]	[0.491]	[−1.113]	[−1.761 *]	[−1.740 *]	[1.414]	
$CAR_{7,10}$	−0.152	0.034	0.006	0.100	−0.021	−0.580	−0.002	1.010	0.71%
	[−2.385 *]	[1.321]	[0.537]	[0.240]	[−0.488]	[−0.659]	[−1.250]	[1.337]	
$CAR_{8,10}$	−0.135	0.037	0.006	0.223	−0.027	0.211	−0.002	0.980	0.55%
	[−2.229 *]	[1.447]	[0.600]	[0.556]	[−0.675]	[0.267]	[−1.284]	[1.393]	
$CAR_{9,10}$	−0.079	0.044	0.015	0.328	0.005	0.154	0.000	0.111	0.44%
	[−1.132]	[1.840 *]	[1.289]	[0.761]	[0.136]	[0.187]	[−0.262]	[0.158]	
Panel B: Negative Informed Shocks									
$CAR_{1,10}$	0.355	−0.052	0.512	−0.030	0.090	−4.166	0.004	−0.226	5.78%
	[5.068 ***]	[−2.056 **]	[2.884 ***]	[−3.173 ***]	[2.064 **]	[−5.651 ***]	[2.068 **]	[−0.266]	
$CAR_{2,10}$	0.332	−0.039	0.322	−0.023	0.053	−3.790	0.003	0.359	5.55%
	[5.227 ***]	[−1.728 *]	[1.919 *]	[−2.556 **]	[1.375]	[−5.823 ***]	[1.850 *]	[0.479]	
$CAR_{3,10}$	0.305	−0.039	0.377	−0.016	0.031	−3.814	0.003	0.666	5.00%
	[4.994 ***]	[−1.811 *]	[2.180 **]	[−1.881 *]	[0.818]	[−5.860 ***]	[1.595]	[0.903]	
$CAR_{4,10}$	0.271	−0.024	0.395	−0.019	0.067	−3.593	0.003	−0.001	4.56%
	[4.273 ***]	[−1.130]	[2.283 **]	[−2.123 **]	[1.668]	[−5.408 ***]	[1.675 *]	[−0.001]	
$CAR_{5,10}$	0.292	−0.023	0.375	−0.015	0.061	−3.414	0.003	0.164	4.45%
	[4.571 ***]	[−1.087]	[2.200 **]	[−1.706 *]	[1.559]	[−5.082 ***]	[1.516]	[0.213]	
$CAR_{6,10}$	0.252	−0.003	0.390	−0.020	0.094	−3.291	0.003	−0.475	4.00%
	[3.992 ***]	[−0.152]	[2.228 **]	[−2.180 **]	[2.352 **]	[−4.634 ***]	[1.449]	[−0.587]	
$CAR_{7,10}$	0.149	0.016	0.173	−0.006	0.026	−2.324	0.001	0.306	1.65%
	[2.444 **]	[0.834]	[1.051]	[−0.675]	[0.716]	[−3.432 ***]	[0.898]	[0.423]	
$CAR_{8,10}$	0.094	0.020	0.064	−0.004	0.036	−1.605	0.001	−0.069	0.84%
	[1.496]	[1.014]	[0.382]	[−0.487]	[0.931]	[−2.480 **]	[0.442]	[−0.091]	
$CAR_{9,10}$	0.084	0.021	0.088	−0.005	0.055	−0.793	−0.001	−0.385	0.61%
	[1.435]	[0.965]	[0.532]	[−0.544]	[1.393]	[−1.248]	[−0.502]	[−0.541]	
Panel C: Positive Uninformed Shocks									
$CAR_{1,10}$	−0.247	−0.006	−0.703	−0.001	−0.019	−2.732	−0.001	1.259	1.63%
	[−6.568 ***]	[−0.390]	[−1.922 *]	[−0.238]	[−0.812]	[−3.193]	[−0.826]	[3.055]	
$CAR_{2,10}$	−0.176	0.003	−0.578	0.000	−0.025	−2.519	0.000	1.088	1.14%
	[−5.288 ***]	[0.254]	[−1.760 *]	[−0.092]	[−1.191]	[−3.192]	[−0.167]	[2.892]	
$CAR_{3,10}$	−0.175	0.001	−0.447	0.001	−0.027	−2.342	−0.001	1.134	1.09%
	[−5.610 ***]	[0.097]	[−1.412]	[0.145]	[−1.338]	[−2.981]	[−0.716]	[3.106]	
$CAR_{4,10}$	−0.198	0.006	−0.490	0.000	−0.023	−2.308	−0.002	1.188	1.32%
	[−6.368 ***]	[0.463]	[−1.541]	[0.028]	[−1.210]	[−2.906]	[−1.657]	[3.351]	
$CAR_{5,10}$	−0.170	−0.003	−0.427	−0.004	−0.010	−2.312	−0.001	0.888	1.08%
	[−5.191 ***]	[−0.242]	[−1.182]	[−0.863]	[−0.520]	[−2.825]	[−1.339]	[2.453]	
$CAR_{6,10}$	−0.148	−0.008	−0.401	−0.007	0.005	−2.563	−0.001	0.592	0.99%
	[−4.386 ***]	[−0.585]	[−1.084]	[−1.385]	[0.256]	[−3.034]	[−1.164]	[1.604]	
$CAR_{7,10}$	−0.067	0.011	0.011	−0.007	0.010	−1.438	0.000	0.116	0.24%
	[−2.235 **]	[0.874]	[0.039]	[−1.446]	[0.531]	[−1.742]	[0.053]	[0.354]	

Table A3. *Cont.*

	AR_0	$SE{\cdot}AR_0$	*Mom*	*PBR*	*LS*	*Vol*	*Ret*	*Int.*	R^2 (%)
				Panel C: Positive Uninformed Shocks					
$CAR_{8,10}$	−0.035	0.016	0.234	−0.006	0.010	−1.264	0.000	−0.038	0.16%
	[−1.212]	[1.321]	[0.861]	[−1.205]	[0.544]	[−1.596]	[0.528]	[−0.116]	
$CAR_{9,10}$	−0.020	0.006	−0.012	−0.006	0.012	−1.132	0.001	−0.102	0.10%
	[−0.718]	[0.492]	[−0.047]	[−1.273]	[0.578]	[−1.562]	[0.579]	[−0.287]	
				Panel D: Negative Uninformed Shocks					
$CAR_{1,10}$	−0.143	0.007	−0.386	0.014	−0.083	4.311	0.001	0.608	1.68%
	[−2.054 **]	[0.334]	[−1.428]	[1.475]	[−1.804 *]	[3.010 ***]	[0.922]	[0.707]	
$CAR_{2,10}$	−0.077	0.010	−0.335	0.011	−0.069	3.885	0.001	0.664	1.39%
	[−1.117]	[0.512]	[−1.473]	[1.351]	[−1.796 *]	[3.190 ***]	[0.784]	[0.894]	
$CAR_{3,10}$	−0.080	0.010	−0.381	0.010	−0.064	3.839	0.001	0.596	1.33%
	[−1.142]	[0.508]	[−1.733 *]	[1.370]	[−1.793 *]	[3.044 ***]	[0.642]	[0.841]	
$CAR_{4,10}$	−0.070	0.014	−0.299	0.009	−0.060	4.048	0.001	0.529	1.35%
	[−1.025]	[0.703]	[−1.398]	[1.251]	[−1.698 *]	[2.978 ***]	[0.747]	[0.779]	
$CAR_{5,10}$	−0.112	0.010	−0.364	0.011	−0.078	4.529	0.001	0.647	1.89%
	[−1.851 *]	[0.541]	[−1.565]	[1.446]	[−2.053 **]	[3.520 ***]	[0.657]	[0.918]	
$CAR_{6,10}$	−0.144	0.011	−0.421	0.011	−0.088	5.359	0.001	0.700	2.29%
	[−2.321 **]	[0.542]	[−1.501]	[1.360]	[−1.995 **]	[3.864 ***]	[0.425]	[0.865]	
$CAR_{7,10}$	−0.077	0.010	−0.402	0.006	−0.069	4.424	0.000	0.715	1.55%
	[−1.385]	[0.568]	[−1.585]	[0.939]	[−2.133 **]	[3.365 ***]	[0.129]	[1.231]	
$CAR_{8,10}$	−0.060	0.016	−0.247	0.011	−0.074	4.386	−0.001	0.907	1.42%
	[−1.146]	[0.904]	[−1.125]	[1.886 *]	[−2.236 **]	[3.510]	[−1.118]	[1.541]	
$CAR_{9,10}$	−0.074	0.012	−0.136	0.010	−0.064	4.071	−0.001	0.687	1.24%
	[−1.323]	[0.660]	[−0.626]	[1.520]	[−1.973 **]	[3.467 ***]	[−0.904]	[1.179]	

Notes

1 The number increased to 3214 as of May 2023.

2 Fama (1998) argues that because daily expected returns are close to zero, the choice of the model for expected returns has a minimal impact on the inference of abnormal returns. Consistently, the results of my analysis remain qualitatively robust when alternative models are used, such as simple market models or those incorporating additional momentum factors, as introduced by Fama and French (2016).

3 Wind (Wind Information Co., Ltd., Shanghai China) is a popular financial data provider in China. The company's data and research are frequently quoted by Chinese and international media, in research reports, and in academic papers (https://www.wind.com.cn/mobile/WFT/en.html) (accessed on 9 January 2025).

4 There have been 55 significant increases in daily returns observed in the CSI All Share Index from 1 May 2016 to 30 April 2023. Notably, sector-wide shocks are not omitted from this dataset, as these price events lie within the focal area of interest for this study. Instead, adjustments are made in the estimation method to accommodate potential clustered effects.

5 In China, ST (Special Treatment) and ST* (Special Treatment*) are labels given to stocks that are subject to different sets of price limits and reporting requirements imposed by the market regulator. These labels are assigned to companies facing financial and operational difficulties.

6 There has been a daily price change limit of ∓10%, except for IPOs, imposed by the mainland China stock exchanges since December 1996.

7 As an illustration, the top three sectors account for 44% of all listed stocks in mainland China's stock market, while the real estate and telecommunication service sectors together comprise approximately 4% of the listed stocks.

8 Savor (2012) also looks for the release of analyst reports on the event and adjacent trade days to determine whether a price event is motivated by information.

9 A text analysis program is written to scan the content of news reports, ensuring their relevance to the company behind the price shocks and confirming that the sentiment of the news aligns with the direction of the price shock.

10 In exceptional cases, individual stocks within the pilot program may remain "non-shortable" due to the absence of share lenders.

11 This information can be obtained from the company's most recent quarterly report or from Wind's statistical data source.

12 Bai and Qin (2015) focus on earnings announcement events, while my study centers on price shock events, considering both those with and without news content.

13 To maintain conciseness, I focus my reporting on post-shock returns within the 10-day horizon, as results beyond this period generally lack statistical significance.

14 A total of 645 (out of 10,335) price events are excluded from the calculation. The underlying shares for the excluded events are largely held by non-financial companies and therefore the shares cannot be borrowed for short sales. Including these events in my analysis would confound my results, as they do not reflect short sellers' responses to the events.

15 There are 17,848 price events under this screening reequipment.

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