

# Opening Price Manipulation and its Value Influences

Jie Liu<sup>a</sup>; Chonglin Wu<sup>a</sup> ; Lin Yuan<sup>b</sup>; Jia Liu<sup>c\*</sup>

<sup>a</sup> School of Economics and Management, Fujian Agriculture and Forestry University, China

<sup>b</sup> Guanghua School of Management, Peking University, China

<sup>c</sup> Business School, University of Birmingham, England, UK

Jie Liu

School of Economics and Management

Fujian Agriculture and Forestry University Fuzhou, China

[liujie@fafu.edu.cn](mailto:liujie@fafu.edu.cn)

Chonglin Wu

School of Economics and Management

Fujian Agriculture and Forestry University, Fuzhou, China

[wuchonglin@fafu.edu.cn](mailto:wuchonglin@fafu.edu.cn)

Lin Yuan

Guanghua School of Management, Peking University Beijing, China

[yuanlin0323@pku.edu.cn](mailto:yuanlin0323@pku.edu.cn)

Jia Liu<sup>\*</sup>

Business School, University of Portsmouth, PO1 3DE, England, UK

[jia.liu@port.ac.uk](mailto:jia.liu@port.ac.uk)

**\*Corresponding author.**

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All remaining errors are our own.

## **Opening Price Manipulation and its Value Influences**

### **Abstract**

We investigate how opening price manipulation influences market behaviors and investors' returns. Analyzing direct evidence comprising 87 opening price manipulation cases, and indirect evidence consisting of 19,003 suspected cases detected by an opening price manipulation identification model that we construct, we examine the impact of manipulation on mispricing, investors' welfare, trading activity and price volatility. Our results indicate that manipulated stocks experience significantly lower returns and a higher probability of price reversal after manipulation. Investors who purchase manipulated stocks at their opening price, or the volume-weighted average price, on the manipulation day make losses on their investments. Further, manipulation increases market trading activity and price volatility due to the influx of retail investors. Our additional analysis demonstrates that enhancing the intensity of external supervision and internal governance can mitigate mispricing caused by opening price manipulation. Our study provides novel evidence of the economic consequences of open market manipulation and policy implications for governments and regulators to develop effective supervisory processes to reduce manipulation and mitigate its impact on efficient markets.

*Keywords:* Opening Price Manipulation; Mispricing; Investors' Welfare; Corporate Governance; Market Supervision

*JEL Classifications:* G12, G14, G20

## 1 Introduction

Market manipulation has engaged the increasing attention of researchers and regulators because it damages the efficiency and integrity of financial markets (Khwaja and Mian, 2005; Cumming et al., 2020). This process, which can be employed as a trading strategy for the purpose of aligning stock prices with manipulators' interests (Cherian and Jarrow, 1995), reduces the accuracy of pricing and liquidity, undermining market efficiency (Kyle and Viswanathan, 2008). Regulatory authorities worldwide have made prodigious efforts to outlaw market manipulation and increase market efficiency (Comerton-Forde and Rydge, 2006a; Cumming et al., 2011). However, instances of price manipulation are still frequently identified, most notably in emerging markets (Khwaja and Mian, 2005; Neupane et al., 2017). Although Jiang et al. (2005) argue that the "stock pools" in the United States in the 1920s cause no damage to market quality, a predominance of prior literature contends that market manipulation reduces pricing accuracy and market fairness (e.g., Comerton-Forde and Putnins, 2011; Li et al., 2020; Cong et al., 2020). Given the grave consequences of such behaviors, we investigate whether, and how, opening price manipulation influences market pricing and trading, and the extent to which it impacts investors' welfare, our primary focus being the economic consequences of this form of malpractice.

Extant research demonstrates that manipulators adopt a "pump-and-dump" trading strategy to manipulate prices in open markets (Aggarwal and Wu 2006; Huang and Cheng, 2015; Khwaja and Mian, 2005; Neupane et al., 2017). Typically, the manipulator drives up the opening price by placing fictitious orders during the pre-opening call auction session to mislead other investors into believing that the stock price change is information-driven.<sup>1</sup> A pre-opening call auction links an overnight non-trading period with a continuous auction and is crucial to the market's absorption of both public and private overnight information (Barclay and Hendershott, 2008; Cao et al., 2000; Moshirian et al., 2012). If the opening price, which should reflect this overnight information, is distorted, there will be a substantial price adjustment, and bid-ask spread and volatility will be enlarged (Pagano et al., 2013).

While acknowledging that prior literature has extensively investigated market manipulation, our research concentrates on the value influences of opening price manipulation, which has not previously been considered. Early investigations typically focus on types of market manipulation such as spoofing (Lee et al., 2013; Kong and Wang, 2014), "stock pools"

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<sup>1</sup> The document *Beware of Risks Associated with Buying New Stocks and Opening Price Manipulation* published in 2015 by the China Securities Regulatory Commission (CSRC) reminds retail investors to pay attention to the trap of manipulated opening price. See <http://www.csrc.gov.cn/csrc/c100211/c1452067/content.shtml> for the full report.

manipulation (Jiang et al., 2005), closing price manipulation (Comerton-Forde and Putnins, 2011, 2014; Cumming et al., 2020; Suen and Wan, 2021), IPO manipulation (Neupane et al., 2017) and financial intermediary manipulation (Khwaja and Mian, 2005). However, they give insufficient weight to opening price manipulation, a common type of market manipulation undertaken during a pre-opening call auction. Our study extends previous work by examining the influence of opening price manipulation on market behaviors and investors' returns and addresses the following research questions: (1) How will opening price manipulation affect stock price performance? (2) What are the influences of opening price manipulation on trading activity and price volatility? (3) Does external supervision and internal governance, enforced by analysts following and independent directors, effectively mitigate the degree of price distortion caused by manipulation?

In seeking answers to our research questions, we examine the influence of opening price manipulation by analyzing both direct evidence, consisting of 87 opening price manipulation cases disclosed by the China Securities Regulatory Commission (CSRC) from 2009 to 2019; and indirect evidence comprising 19,003 suspected cases detected by applying a manipulation identification model. To examine the effect of opening price manipulation without the interference of overnight information, we select non-manipulated stocks, whose overnight price gaps are similar to those of the manipulated stocks, as the control group. Our results clearly indicate that opening price manipulation causes mispricing, leading to a significant difference in performance between the manipulated stocks and the non-manipulated stocks following manipulation. Our further analyses demonstrate that in comparison to stocks in the control group, 1) the 5-day cumulative abnormal returns ( $\Delta$ ) of manipulated stocks are significantly lower than those of non-manipulated stocks by 210 basis points and 100 basis points, respectively, as our direct and indirect evidence indicate. The probability of the price falling below the opening price of manipulated stocks is significantly higher by 12.83% and 16.92% than that of non-manipulated stocks. Investors who buy manipulated stocks at the opening price during a call auction, or at volume-weighted average price on the day of manipulation, make a loss of 413 basis points or 426 basis points, respectively, in the following 5 trading days. 2) Opening price manipulation increases stock trading activity. In comparison with stocks in the control group, the turnover rate for manipulated stocks is significantly higher, while the Amihud illiquidity ratio is significantly lower. 3) Manipulated stocks attract an influx of retail investors, with an inflow 6.4% and 1.0% higher than that of stocks in the control group, which subsequently causes price volatility to increase by 2.2% and 0.8%, respectively, as indicated by our direct and indirect evidence. 4) Enhancing the intensity of external supervision and internal

governance can reduce the degree of mispricing caused by opening price manipulation. Stocks with strong external supervision, such as those with intense analyst scrutiny and those issued by firms audited by the Big Four accounting firms, have a lower degree of mispricing due to opening price manipulation. Similarly, stocks with strong corporate governance, such as those of non-state-owned enterprises and those of firms with a high proportion of independent directors on their boards, have a lower degree of mispricing due to opening price manipulation.

Our study has made valuable contributions to the literature in the following respects: first, existing empirical research has already explored types of market manipulation such as spoofing (Lee et al., 2013; Kong and Wang, 2014), “stock pools” manipulation (Jiang et al., 2005), closing price manipulation (Comerton-Forde and Putnins, 2011, 2014; Cumming et al., 2020; Suen and Wan, 2021), IPO manipulation (Neupane et al., 2017) and financial intermediary manipulation (Khwaja and Mian, 2005). However, while there is a wealth of literature on market manipulation, opening price manipulation has not attracted sufficient academic interest. Our study closes this research lacuna in the existing literature by investigating the economic consequences of opening price manipulation. Albeit this practice is one of the forms of “spoofing” or “fictitious order manipulation”, extant literature (Kong and Wang, 2014; Lee et al., 2013) does not distinguish the trading sessions during which manipulation occurs. Since there are significant differences in trading rules between the pre-opening call auction session and the continuous auction session<sup>2</sup>, which may prejudice the estimation results if the samples are intermingled, it is more informative to study spoofing during these two trading sessions separately. Accordingly, our study focuses on manipulation during the pre-opening call auction session in relation to 87 cases disclosed by the CSRC, and is, to the best of our knowledge, the first specialized research into the economic consequences of opening price manipulation. In addition, the market manipulation cases investigated and disclosed by regulators account for only a small proportion of all cases (Comerton-Forde and Putniņš, 2014; Neupane et al, 2017). Research using direct evidence may confront the complication of sample selection bias. Therefore, we construct an opening price manipulation identification model to detect suspected manipulation cases by identifying features such as overnight abnormal gaps, stock price

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<sup>2</sup> The Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) in China use a centralized, scripless, computerized order matching system instead of market makers as in NYSE (Wang et al., 2019). In the pre-opening session from 9:15 to 9:30, the periodic auction is used to determine opening prices. The bid prices and lots from the buyer side and ask prices and lots from the seller side are collected to form the demand and supply schedule. The opening price is set in order to maximize the trading volume and equate the quantity supplied to quantity demanded. After that, the SSE and SZSE open at 9:30 and close at 15:00 with a lunch break from 11:30 to 13:00. The continuous and discriminating auction method is used based on the supply schedule and the demand schedule. The auction is continuous throughout the trading day, which is discriminating in the sense that orders are placed on the demand and supply schedules on the first-in-first-out basis (FIFO).

reversals, large order cancellations, and non-fundamental-information conditions. Further, the construction of the identification model also makes it possible to use additional data disclosed by the regulator to examine the impact of opening price manipulation. Moreover, the identification model that we have constructed incorporates the ability to avoid delays in enforcement, and it is uniform, being unbiased by enforcement differences across firms over time. Furthermore, a call auction is the most common mechanism for determining the opening price, but it can also be used as a convenient tool by market manipulators, especially when investors are allowed to cancel their submissions (Comerton-Forde and Rydge, 2006b; Biais et al., 2014). Overall, our research findings contribute significantly to an in-depth understanding of the call auction mechanism and are beneficial for market regulators seeking to improve its functioning.

The rest of the paper is structured as follows: Section 2 reviews the literature and constructs the hypotheses. Section 3 discusses the research methods, including the data, sample and main variables. Section 4 presents and discusses the empirical results. Section 5 concludes the study.

## **2 Literature review and hypothesis development**

### **2.1 Literature review**

Information theory proposes that manipulators can mislead other investors into believing that a stock price change is information-driven (Allen and Gorton, 1992; Comerton-Forde and Rydge, 2006a, 2006b; Hauser et al., 2022). In the presence of information asymmetry, it is not difficult for manipulators to conceal their real identities and pretend to be informed traders during information-intensive periods (Allen and Gale, 1992). Thus, a trade-based manipulation usually takes place during an information-intensive period, such as a pre-opening call auction. Investors who have no access to fundamental information themselves try to infer from prices and volume whether an informed party is buying a stock. As a result, uninformed investors who are attracted by the illusion of high-volume demand for a manipulated stock compete with one another for shares and buy them in the aggregate, which impels the stock price upwards and increases trading activity (Aggarwal and Wu, 2006). Extant research subdivides market manipulation into information-based manipulation and trade-based manipulation, or a combination of the two (Allen and Gale, 1992; Putniņš, 2012). Information-based manipulation is achieved by the dissemination of bogus information (Benabou and Laroque, 1992; Van Bommel, 2003); whereas, trade-based manipulation occurs when agents influence stock prices

or volumes through their own trading behavior (Aggarwal and Wu, 2006; Khwaja and Mian, 2005). The manipulator drives up the stock price by placing fictitious orders during the pre-opening call auction session, thus engaging in a form of trade-based manipulation. Informational theory posits that manipulators in a market with information asymmetry undertake trade-based manipulation to earn profits (Allen and Gale, 1992; Allen and Gorton, 1992).

Empirical research on market manipulation investigates diverse manipulation strategies in different jurisdictions, suggesting varied trading behaviors and economic consequences. Jiang et al. (2005) find that the “stock pools” in the United States in the 1920s cause no damage to market quality. Khwaja and Mian (2005) investigate the trading records of financial intermediaries in Pakistan and determine that brokers use the “pump and dump” manipulation strategy. Neupane et al. (2017) find that a similar strategy is employed by IPO manipulators in the Indian Stock Exchange. Comerton-Forde and Putnins (2011) and Comerton-Forde and Putnins (2014) construct a closing price manipulation identification model to examine manipulations in the US and Canada, arguing that only a small proportion of manipulation has been discovered and the culprits prosecuted. Despite the findings of Jiang et al. (2005), recent evidence demonstrates that such manipulative practices affect market behaviors and damage corporate value. Cumming et al. (2020) establish that end-of-day stock price manipulation reduces incentives for employees to innovate, especially in markets with low intellectual property rights and high shareholder protection. Market manipulation in the cryptocurrency market is also commonly observed. Li et al. (2020) examine pump-and-dump schemes in the cryptocurrency market and find that manipulation leads to short-term price bubbles. Cong et al. (2020) examine the trading records of 29 cryptocurrency exchanges and find that wash trades affect trading volumes and distort prices.

Trading rules and regulatory mechanisms for restraining market manipulation have aroused the interest of researchers. Suen and Wan (2021) examine the effect of call auction design on closing price manipulation, and their results indicate that the standard call auction mechanism is vulnerable to closing price manipulation. Duong et al. (2021) find that market manipulation trading rules reduce IPO underpricing. Kemme et al. (2022) report that the Arrowhead Renewal improvements (ARI) introduce new risk management functions to improve market fairness by reducing manipulative trading strategies.

Further, extant research has examined the call auction, which is a means extensively employed to determine opening prices, closing prices and settlement prices by stock exchanges

in many countries (Chelley-Steeley, 2008; Pagano et al., 2013; Pagano and Swartz, 2003). Comerton-Forde and Rydge (2006b) study closing price manipulation in six developed markets, finding that well-designed algorithms utilized during a call auction, such as volatility extensions, help to reduce closing price manipulation. Similar to the closing price, in most cases the opening price is determined through a call auction. The opening price, which is a reflection of overnight information, is of great importance to investors (Jiang and Zhu, 2017; Moshirian, 2012; Tsiakas, 2008), as it is used as the settlement price for some financial derivatives, although it can be subject to manipulation (Pagano et al., 2013). Clearly, if the adulteration of market processes is to be effectively controlled, and markets to operate efficiently, research into the mechanisms of trading, and how they can be distorted, is urgently required.

## **2.2 Hypotheses development**

Pricing accuracy during a pre-opening call auction is of critical importance to the market's absorption of overnight information. (Cao et al., 2000; Moshirian et al., 2012). To influence opening prices, manipulators submit large-size orders during the pre-opening session at a price far higher than is justified by the fundamental characteristics of a stock, thereby reducing market pricing efficiency. Lee et al. (2013) contend that by submitting such orders that are very unlikely to be finalized, manipulators can deceive investors and manipulate stock prices. Literature on market manipulation argues that stock prices will rise when manipulators drive up prices and fall once they sell the stock (Aggarwal and Wu, 2006; Huang and Cheng, 2015; Khwaja and Mian, 2005; Neupane et al., 2017). Pagano et al. (2013) also observe that an unrealistic opening price is more likely to undergo greater price adjustments soon after a market opens. Therefore, it is arguable that when a stock opens with a price higher than its true arm's length value because of manipulation, the underpinning provided by the stock's fundamentals is relatively weak in comparison to stocks that exhibit a similar overnight gap in pricing, so that the distorted opening price will gradually be corrected to reverse the mispricing and reveal its "true" price (Medrano and Vives, 2001; Hauser et al., 2022). Thus, we predict that, in comparison to non-manipulated stocks that exhibit similar overnight gaps, manipulated stocks will display lower intraday returns on the manipulation day and lower short-term cumulative abnormal returns after manipulation. Furthermore, the stock's price may even fall below its opening price on the manipulation day. Therefore, investors who have purchased the manipulated stock will suffer losses on their investment. Given the foregoing discussions, we propose our first hypothesis below:



**Hypothesis 1a** Manipulated stocks will display lower short-term returns than non-manipulated stocks.

**Hypothesis 1b** Manipulated stocks will display a higher probability of price reversal than non-manipulated stocks.

**Hypothesis 1c** Investors benefits are negatively correlated with the opening price manipulation.

It is evident that manipulators submit large-size orders to influence opening prices and in doing so can also induce trading by speculators and arbitrageurs (Allen and Gale, 1992; Aggarwal and Wu, 2006). For example, an opening price far higher than the previous closing price caused by a manipulator may induce buying by momentum traders or selling by sophisticated investors and arbitrageurs, who seize the opportunity to earn profits by counteracting the manipulator's influence (Comerton-Forde and Putnins, 2011). In particular, uninformed investors who are attracted by the illusion of high-volume demand for a manipulated stock compete with one another for shares and buy them in the aggregate (Khwaja and Mian, 2005; Aggarwal and Wu, 2006; Huang and Cheng, 2015). Therefore, we predict that market trading activity during manipulation and in the short-term thereafter increases in intensity due to the augmentation of trading generated by manipulators' activities, as well as by other investors in the market. This leads to our second hypothesis below:

**Hypothesis 2** Manipulated stocks display higher trading activity both on the day of manipulation and in the short-term thereafter in comparison to non-manipulated stocks.

Extant research suggests that a manipulator's malpractices induce other investors in the market to participate, with the consequence that manipulated stocks tend to be more volatile during both manipulation and post-manipulation periods (Allen and Gale, 1992; Aggarwal and Wu, 2006). Retail investors, who are often regarded as noise traders, usually have no access to fundamental information themselves and therefore strive to determine whether an informed party is buying a stock by inferring information from the trajectories of price and volume (Allen and Gorton, 1992; Hauser et al., 2022). As a consequence, they are more likely to be deceived by a manipulator's swindle. Models predict that noise trading contributes to idiosyncratic volatility above and beyond that engendered by cash flow news (Banerjee and Green, 2015; Brandt et al., 2010; Foucault et al., 2011; Choi et al., 2018). Hence, we posit that an opening price manipulation positively affects stock price volatility if retail investors misled by manipulators purchase shares in the aggregate. This leads to our third hypothesis below:

**Hypothesis 3** Opening price manipulation creates an influx of retail investors, which causes stock price volatility of manipulated stocks to be higher than that of non-manipulated stocks following manipulation.

Lack of information transparency is an essential prerequisite for facilitating market manipulation (Allen and Gale, 1992; Glosten and Milgrom, 1985). Trading-based manipulation is feasible only when there information asymmetry is present in the market (Aggarwal and Wu, 2006) and investors cannot determine whether or not a manipulator's trading is founded on realistic and objective information or on chicanery (Allen and Gale, 1992; Glosten and Milgrom, 1985; Aggarwal and Wu, 2006). External or internal supervisors, such as securities analysts and independent directors, actively participate in mining company information and in monitoring management's behavior, which is crucial for reducing information asymmetry and improving information transparency (Francis et al., 2013; Jiang et al., 2015; Liu et al., 2015; Charitou et al., 2019; Gu et al., 2019). Accordingly, we argue that more effective external supervision and internal governance can help mitigate mispricing caused by market manipulation. Therefore, we propose our fourth hypothesis below:

**Hypothesis 4** Mispricing caused by opening price manipulation is mitigated for firms with more effective external supervision and internal governance.

### **3 Research background and research design**

#### **3.1 Research background**

Trading rules during pre-opening call auctions on the Shanghai and Shenzhen Stock Exchanges are depicted in Figure 1. Between 9:15 and 9:25 a.m., investors are allowed to submit or cancel orders. Between 9:20 and 9:25 a.m., investors can only submit orders, and the stock exchange will determine the opening price based on all effective submissions made before 9:25 a.m. Between 9:25 and 9:30 a.m., the stock exchange will process neither order submissions nor cancellations. At 9:30, the stock exchange opens for continuous auction.

[Insert Figure 1 here]

In opening price manipulation, the manipulator submits orders during the pre-opening call auction at a price higher than either the previous closing price or the market price. Without any real intention of buying the stock, the manipulator submits large quantities of orders to entice other investors to follow suit, and cancels the submissions before orders are finalized, which drives up the opening price much higher than its fundamental value. Thereafter, the

manipulators will gradually sell off all the shares they hold. (Please see Appendix A for more detail on the characteristics of opening price manipulation and a typical case.)

### **3.2 Data and sample**

The main variables for the analyses contain three sets. The first set comprises instances of opening price manipulations extracted from CSRC's administrative penalty orders and detected by our manipulation identification model. The second comprises stock trading data, including opening price, closing price, daily returns and turnover. The third comprises the company's fundamental information, including its market capitalization, the percentage of institutional stockholdings, the book-to-market ratio, and Tobin's Q ratio. Continuous variables are winsorized at the 1% and 99% levels to mitigate the impact of outliers. These data are obtained from the China Stock Market and Accounting Research Databases (CSMAR) and the RESSET Database. Detailed definitions of the main variables are listed in Appendix B.

### **3.3 Main independent variables**

#### **3.3.1 Direct empirical evidence: Real cases disclosed by the CSRC**

The instances of opening price manipulations are extracted from administrative penalty orders issued by CSRC between January 2009 to December 2019. It is noteworthy that these cases, in fact, took place between 2007 and 2017. The disclosure of a case by the CSRC is much later than the occurrence of the case due to the long and complex regulatory process<sup>3</sup>. To eliminate the possible influence of confounding events that might affect stock prices or liquidity during the event window, we exclude from the research sample any examples of manipulation occurring in the 20 days before or 20 days after major events<sup>4</sup>. The latter include mergers and acquisitions, equity changes, earnings announcements and so on, which are obtained from the RESSET database. Appendix C presents the data specifying the cases of manipulation, together with the names and codes of stocks involved as well as the penalty order document number for all 87 cases of opening price manipulation. To examine the effect of opening price manipulation without the interference of overnight information, we take non-manipulated stocks whose overnight price gaps are similar to those of the manipulated stocks as the control

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<sup>3</sup> Before issuing a penalty order, the supervisory body needs to go through a series of steps to process a market manipulation case including establishing a case, investigation, prosecution and trial in court, which delays the disclosure of the CSRC's penalty order to later than the occurrence of the manipulation case. For example, the case of Gohigh Data Networks Technology (CSRC Order # (2018)108) disclosed in 2018 actually took place in 2014.

<sup>4</sup> About the summary of major events, please refer to the data specification sheets in the RESSET database. Please refer to <http://db.resset.com/db/download/dataDictionary.jsp?tableName=CMAJEVENT>.

group<sup>5</sup>. Our final sample based on direct evidence comprises 23,330 stock-day observations for the empirical analysis.

### 3.3.2 Indirect empirical evidence: Suspected cases detected by the identification model

Market manipulation cases investigated and disclosed by regulators account for only a small proportion of all cases. There is a great deal of manipulation in the market that has escaped detection and punishment by the regulator (Comerton-Forde and Putniņš, 2014; Neupane et al, 2017). Research based on direct evidence, which consists of cases disclosed by market regulators, may therefore face the problem of sample selection bias.

To reduce the impact of this, we construct an opening price manipulation identification model. Based on suspected manipulation cases detected by this model (indirect evidence), we evaluate the impact of manipulation on mispricing, trading activity, and volatility. Specifically, we take account of four identification features, which are abnormal overnight gaps, stock price reversals, large withdrawals, and a lack of fundamental information (Medrano and Vives, 2001; Cumming et al., 2020; Hauser et al., 2022) to construct an identification model to detect suspected cases of manipulation.

(1) An abnormal overnight gap<sup>6</sup> occurs when the opening price is significantly higher than the closing price of the previous trading day. We calculate the mean and standard deviation of overnight gaps in the previous 30 trading days. If the overnight gap of the day exceeds the mean by 3 standard deviations, it is considered to be an abnormal overnight gap (Medrano and Vives, 2001).

(1)

where  $g_{i,t}$  is the overnight gap of stock  $i$  on day  $t$ , and  $\mu$  is the mean and standard deviation of the overnight gaps in the previous 30 trading days.

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<sup>5</sup> To be more specific, we calculate the overnight jump return which is rounded to percent, and chooses non-manipulated stocks displaying the same overnight return as the control group.

<sup>6</sup> The literature observes that liquidity is an important factor affecting overnight gaps, especially in China. For example, Qiao and Dam (2020) report a puzzling phenomenon in that the overnight returns for the Shanghai Stock Exchange and the Shenzhen Stock Exchange are significantly negative, violating the asset pricing model. They argue that the “T+1” trading rule in China explains this puzzle. Their findings could cast doubt on our identification model, as a high overnight gap might not be due to the manipulated cases but because that some large buyers may require a discount to purchase the stock during the next trading day under the “T+1” rules. In order to overcome the systematic impact of illiquidity on overnight gaps, Akbas et al. (2021) calculate their main variable of interest (daytime reversal) scaled by the average value over the prior 12 months. Consistent with Akbas et al. (2021), an “abnormal overnight gap” in our paper is defined as a dummy variable indicating whether the overnight gap of the day exceeds the mean by 3 standard deviations over the prior 30 trading days. This algorithm can eliminate the systematic influence of illiquidity on an overnight gap. On the other hand, we concede that the identification model cannot distinguish whether a high overnight gap is due to unsystematic illiquidity or market manipulation, which can affect the accuracy of the model.

(2) Intraday price reversal (Hauser et al., 2022), as a dummy variable indicating whether the magnitude of the intraday price reversal reached 50% of the overnight gap.

(2)

(3) Abnormal cancellation of orders. Between 9:15 and 9:20, investors cancelled orders in unusually large numbers. Similar to the definition of an abnormal overnight gap, abnormal order cancellation is defined as when the number of orders cancelled on a day exceeds the mean by 3 standard deviations of the previous 30 trading days.

(4) No fundamental information, indicating that there are no stock-related information disclosures and major fundamental events.

Applying the identification model, we have detected 19,003 suspicious opening price manipulation cases from 2007 to 2017. Consistent with Comerton-Forde and Putniņš (2014) and Neupane et al. (2017), manipulation cases investigated and disclosed by regulators account for only a small proportion of actual occurrences. To verify the effectiveness of the identification model, we compare the suspected cases that it detects with the 87 cases disclosed by the CSRC. The results demonstrate that 54 cases can be detected by the manipulation identification model, and that the identification success rate is 62.07%<sup>7</sup>. We take non-manipulated stocks whose overnight price gaps are similar to those of the manipulated stocks as the control group. These procedures yield 1,172,982 stock-day observations in total for our empirical analyses.

### **3.4 Main dependent variables**

#### **3.4.1 Mispricing and investors' losses**

In an efficient market, overnight price gaps should be a timely and accurate reflection of overnight information in the market (Cao et al., 2000; Moshirian et al., 2012). However, opening price manipulation obstructs accurate reactions of market prices to overnight information. Therefore, price distortions will be gradually corrected after manipulation (Medrano and Vives, 2001; Hauser et al., 2022). Thus, we use post-manipulation stock returns

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<sup>7</sup> We acknowledge that the identification measures may be biased by non-manipulation factors. For instance, a high abnormal overnight gap might be due to illiquidity during the previous trading day. Although the algorithm of “abnormal” overnight gap cannot completely resolve this issue, it can serve as an effective way to address the concern that the overnight return in China is significantly negative for the illiquidity as a result of the “T+1” trading rule (Qiao and Dam, 2020). Meanwhile, the success rate of our model is similar to that in the extant literature. Liu et al. (2021) use a support vector machine model (SVM) to detect manipulation in China, whose success rate is 60.11% [see Section 5.1]. Based on the model proposed by Aitken et al. (2015), Li et al. (2018) identify the closing price manipulation in China with a success rate of 59.26% [see Section 4.1].

as a measurement of mispricing caused by manipulation. For example, when opening price manipulation causes a stock's opening price to rise above its fundamental value, the stock price will gradually decline to reveal the stock's true value, either on the day of manipulation or in the following trading days. The more a stock's price drops after manipulation, the greater is the discrepancy between the opening price and the fundamental value. We adopt three indicators to measure stock performance after manipulation. The first is intraday abnormal return on the day of manipulation ( $AR_{it}$ ). The second is the 5-day cumulative abnormal return after manipulation ( $CAR_{it}$ ). The third is a dummy variable indicating whether price reversal occurs after manipulation ( $PR_{it}$ ). In summary, we contend that if distortion exists in the opening price of the manipulated stock on the day of manipulation, once the manipulation is complete, the market will begin to correct the distortion so that the stock's price will return to its fundamental value. This suggests that in comparison with stocks in the control group, manipulated stocks will have a lower intraday return ( $AR_{it}$ ), lower ( $CAR_{it}$ ), and a higher likelihood of price reversal ( $PR_{it}$ ).

To estimate hypothetical investors' losses, we use two measures for calculating the cost incurred by investors when they purchase manipulated stocks. The first is the opening price on the day of manipulation ( $P_{it}$ ), measuring the average cost of buying shares of the manipulated stock during the pre-opening call auction. The second is the volume-weighted average price on the day of manipulation ( $VWAP_{it}$ ). In addition, we use the closing price on the trading day following the day of manipulation as a means of measuring the hypothetical selling price. Thus, the hypothetical investors' losses ( $L_{it}$ ) for those who purchase manipulated stocks during a pre-opening call auction, and the hypothetical investors' losses ( $L_{it}$ ) for those who purchase manipulated stocks at the cost of volume-weighted average price, are calculated based on the hypothetical purchase price and selling price.

### **3.4.2 Trading activity**

We employ abnormal turnover ( $AT_{it}$ ) and the Amihud ratio ( $AR_{it}$ ) on the manipulation day to measure market trading activity (Amihud, 2002; Mayer, 2021). Similarly, we use cumulative abnormal turnover ( $CAT_{it}$ ) and the Amihud ratio ( $AR_{it}$ ) for 5 trading days after manipulation to measure market trading activity after manipulation.

### **3.4.3 Stock price volatility**

Following Che (2018), we use idiosyncratic volatility ( $IV_{it}$ ) as a measurement of volatility. Hypothesis 3 proposes that opening price manipulation attracts an influx of retail traders, causing the stock's volatility after manipulation to be higher than that of the control group. To test the hypothesis, we use the net inflow ratio of retail trading ( $NI_{it}$ ) to determine the direction in

which cash in the stock market is flowing. Compared with institutional investors, the trading size of individual investors is much smaller. Therefore, we consider orders with a trading size of less than 1 million RMB<sup>8</sup> to be retail trading.

### 3.5 Control variables

Prior research documents that firms in relatively weaker financial condition are more likely to be targeted by manipulators (Chakraborty and Yilmaz, 2004; Khwaja and Mian, 2005). Therefore, we first include firm size ( $\ln(\text{SIZE})$ ), return on assets ( $\text{ROA}$ ), the market-to-book ratio ( $\text{M/B}$ ) and Tobin's Q ratio ( $\text{Q}$ ) as controls, as we expect them to affect the economic consequence of market manipulation (Huang and Cheng, 2015). Further, external and internal monitoring are expected to mitigate the effect of market manipulation (Brandt et al., 2010; Gu et al., 2019). Following Comerton-Forde and Putniņš (2014), we control for a set of governance mechanisms, including the percentage of institutional stockholdings ( $\text{INST}$ ) and the number of analysts following ( $\text{ANALYST}$ ). Moreover, we include past turnover ( $\text{TURN}$ ) and the past Amihud illiquidity index ( $\text{AMIHUD}$ ) to control for their effects on the trading activity after manipulation (Comerton-Forde and Putniņš, 2011). As stock price volatilities are auto-correlated, we add control variables that may affect volatility, such as intraday volatility ( $\text{IVOL}$ ), past stock return volatility ( $\text{PVOL}$ ), and absolute stock return ( $\text{ABSRET}$ ), following Comerton-Forde and Putniņš (2014). Furthermore, as stock price may impact stock volatility (Brandt et al., 2010; Banerjee and Green, 2015; Ma et al., 2022; Ye et al., 2019; Chen et al., 2021), we also control for stock price ( $\text{PRICE}$ ) (Lee et al., 2013; Foucault et al., 2011). Finally, we control for year fixed effect and industry fixed effect (Neupane et al., 2017).

### 3.6 Descriptive statistics

Table 1 provides descriptive statistics for the main independent variables, main dependent variables and control variables, including the sample size, mean value, standard deviation, smallest value, first quartile, second quartile, third quartile, and largest value. Panels A and B report summary statistics for the manipulation cases of direct evidence and indirect evidence, respectively.

To determine the characteristics of manipulators' targets, we compare manipulated stocks against stocks in the control group, examining the difference between the two in terms of fundamental characteristics based on direct evidence. Mean difference test results are shown in Panel C of Table 1. In comparison with non-manipulated stocks, manipulated stocks are issued by smaller firms and attract less analyst attention. Existing research suggests that whether or

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<sup>8</sup> According to Shanghai Stock Exchange Statistics Annual (2020), 93.05% of individual investors have securities assets worth less than 1 million RMB. Please refer to <http://www.sse.com.cn/aboutus/publication/yearly/> for more details.

not a manipulator can successfully manipulate the market depends on the degree of information asymmetry (Chakraborty and Yilmaz, 2004; Fishchel and Ross, 1991; Khwaja and Mian, 2005). Hence, manipulators often choose stocks with lower information transparency as their target, such as those of firms with a smaller market cap (Lee et al., 2013; Huang and Cheng, 2015) or with fewer analysts following (Charitou et al., 2019; Gu et al., 2019).

[Insert Table 1 here]

## **4 Empirical results and discussions**

### **4.1 Influence of opening price manipulation**

#### **4.1.1 Mispricing and investors' value losses**

On the premise that a manipulation drives a stock's opening price higher than its fundamental value, we predict that stock price will fall after manipulation. To visually observe the mispricing caused by an opening price manipulation, we compare the difference of price performance between manipulated stocks and non-manipulated stocks based on direct evidence. As depicted in Figure 2, where the opening price manipulation on day (T+0) is divided into the pre-opening call auction session (T+0 Opn) and the continuous trading session (T+0 Cls), the stock price of the manipulation group gradually decreases following the call auction session on the day of manipulation. On the fifth trading day (T+5) after the manipulation, the cumulative stock return of the manipulation group drops to 121 basis points, while the cumulative stock return of the control group rises to 363 basis points, so that the difference between the two reaches -242 basis points, indicating that the mispricing has been gradually corrected after the opening price manipulation, supporting our Hypothesis 1a.

[Insert Figure 2 here]

Mean difference tests in Appendix D report that intraday returns on the day of manipulation () of stocks are lower than those of the control group, although the difference in direct evidence is statistically insignificant. Further, 5-day cumulative abnormal returns after manipulation () of manipulated stocks are significantly lower, while the probability of price reversal is significantly higher. To subject these results to more formal testing, Model (3) and Model (4) are used to estimate the influence of opening price manipulation on intraday returns on the manipulation day and cumulative abnormal return after manipulation, as specified in Model (5), to estimate the influence on the probability of price reversal.

(3)

(4)



(5)

where the dependent variable represents the intraday return on the day of manipulation. represents 5-day cumulative abnormal return after manipulation. is a dummy variable indicating whether the stock price on the fifth day after manipulation falls below its opening price on manipulation day. The key independent variable is equal to 1 if the stock is manipulated, and 0 otherwise. comprises various control variables that may affect stock returns. Following prior studies (Chakraborty and Yilmaz, 2004; Khwaja and Mian, 2005; Jiang et al., 2005; Comerton-Forde and Putniņš, 2011; Lee et al., 2013; Huang and Cheng, 2015; Neupane et al., 2017), we control for price (), past turnover (), intraday volatility (), past stock return volatility (), the company's size (), the percentage of institutional stockholdings (), the number of analysts following (), the market-to-book ratio (), return on assets (), and Tobin's Q ratio (). is the error term.

The estimation results are shown in Table 2. Columns (1) - (3) report empirical results based on direct evidence, and columns (4) - (6) report empirical results based on indirect evidence. The OLS estimation results for Model (3) are reported in columns (1) and (4), showing that the intraday return on manipulation day of manipulated stocks is lower than control group stocks by 610 basis points, as indicated by indirect evidence, though the difference in direct evidence is statistically insignificant. Columns (2) and (5) report the OLS estimation results for Model (4), which reveal that the 5-day cumulative abnormal returns () of manipulated stocks are significantly lower than those of control group stocks by 210 basis points and 100 basis points, respectively, as indicated by direct and indirect evidence. The result is not only statistically significant, but is also of economic importance, because it demonstrates that the performance of manipulated stocks is weaker in comparison to that of control group stocks after the manipulator leaves. Furthermore, column (3) and column (6) report the Probit model estimation results for Model (5), which show that there is a higher probability that manipulated stocks will experience a price reversal. The probability of manipulated stocks having their price after manipulation fall below their opening price on the manipulation day () is higher than that of control group stocks by 12.83% and 16.92%, respectively, as indicated by direct and indirect evidence. These results confirm that manipulation distorts the opening price, causing it to deviate from the stock's fundamental value. The distorted price will be gradually corrected after manipulation, which is in line with early studies (e.g., Aggarwal and Wu, 2006; Huang and Cheng, 2015; Khwaja and Mian, 2005; Neupane et al., 2017), providing support for Hypotheses 1a and 1b.

[Insert Table 2 here]

Furthermore, we estimate investors' losses caused by manipulation based on direct evidence. In Table 3, columns (1) and (4) present the results of the average purchase price of investors during the pre-opening call auction on manipulation day ( $P_{t,0}$ ), the average purchase price on manipulation day ( $P_{t,1}$ ), and the corresponding position value, respectively. The hypothetical average purchase price is then compared with the closing price on the third and fifth days after manipulation ( $P_{t,3}$  and  $P_{t,5}$ ) to estimate the losses incurred by investors. Investor losses are estimated both as an amount and as a percentage. Columns (2) and (3) report the investor's loss ( $L_{t,1}$ ) calculated with the opening price on manipulation day as the hypothetical average purchase price, and columns (5) and (6) report the investor's loss ( $L_{t,2}$ ) calculated with the volume-weighted average price on manipulation day as the hypothetical average purchase price.

The results demonstrate that for investors who bought the manipulated stock at the opening price during pre-opening call auctions on the manipulation day, the average purchase price is 21.78 RMB per share, the average closing price on the third day after manipulation is 21.11 RMB per share, and the average investors' losses are 308 basis points, respectively. In this situation, on average, investors lose 0.24 million RMB ( $L_{t,1}$ ) per manipulation case, as their position value falls from 7.92 million RMB to 7.68 million RMB. On the fifth day after manipulation, the average closing price is 20.88 RMB per share, and the average percentage of losses incurred is 413 basis points. On average, these investors make a loss of 0.33 million per manipulation case and their position value drops from 7.92 million to 7.59 million. For comparison, Comerton-Forde and Putniņš (2011) find that investors who purchase a stock subject to closing price manipulation at the closing price lose 185 basis points on the next trading day.

For investors who buy the manipulated stock at volume-weighted average price on manipulation day, the average trading price is 21.81 RMB per share, with the average closing price being 21.11 RMB per share on the third day after manipulation. The average investors' losses are 321 basis points, or 3.01 million RMB ( $L_{t,2}$ ), and the investors' position value drops from 93.88 million RMB to 90.87 million RMB. Five trading days after manipulation, the average closing price is 20.88 RMB per share, the average investors' losses are 426 basis points, or 4 million RMB, and their position value drop from 93.88 million RMB to 89.88 million RMB. These results demonstrate that both investors who have purchased manipulated stocks at opening price, and those who have purchased manipulated stocks at  $P_{t,1}$ , have suffered

losses on their investments, providing support for Hypothesis 1c.

[Insert Table 3 here]

#### 4.1.2 Trading activity during and after manipulation

We predict that trading activity of manipulated stocks will be higher than that of control group stocks, both on the day of manipulation and after manipulation, which is consistent with the mean difference test results in Appendix D. Model (6) and Model (7) examine the difference in trading activity between manipulated stocks and control group stocks on manipulation day, and Models (8) and (9) investigate the difference in trading activity between manipulated stocks and control group stocks five days after manipulation.

(6)

(7)

(8)

(9)

where the dependent variable  $AT_{it}$  and  $AR_{it}$  represent the abnormal turnover and the Amihud ratio on the day of manipulation, respectively.  $AT_{it+5}$  and  $AR_{it+5}$  represent the 5-day cumulative abnormal turnover and the Amihud ratio after manipulation. The key independent variable,  $MANIP_{it}$ , is equal to 1 if the stock is manipulated, and 0 otherwise.  $X_{it}$  comprises various control variables that may affect trading activity. Following prior studies (Chakraborty and Yilmaz, 2004; Khwaja and Mian, 2005; Comerton-Forde and Putniņš, 2011, 2014; Lee et al., 2013; Huang and Cheng, 2015; Neupane et al., 2017; Gu et al., 2019), we control for price ( $P_{it}$ ), past turnover ( $TURN_{it}$ ), intraday volatility ( $IVOL_{it}$ ), past stock return volatility ( $SRVOL_{it}$ ), absolute stock return ( $ABSRET_{it}$ ), the company's size ( $SIZE_{it}$ ), the percentage of institutional stockholdings ( $INST_{it}$ ), the number of analysts following ( $ANALYST_{it}$ ), the market-to-book ratio ( $MTOB_{it}$ ), return on assets ( $ROA_{it}$ ), and Tobin's Q ratio ( $Q_{it}$ ).  $\epsilon_{it}$  is the error term.

Columns (1) - (4) of Table 4 report empirical results based on direct evidence, and columns (5) - (8) report empirical results based on indirect evidence. Columns (1) and (5) show that on manipulation day, manipulated stocks have a significantly higher abnormal turnover ( $AT_{it}$ ). Columns (2) and (6) indicate that the Amihud illiquidity ratio ( $AR_{it}$ ) of manipulated stocks is significantly lower, consistent with our expectation that trading activity is higher for manipulated stocks than for control group stocks on manipulation day. Similarly, columns (3) and (4) and columns (7) and (8) show that during the five trading days following manipulation, manipulated stocks undergo significantly higher trading activity. In comparison with control group stocks, manipulated stocks have a higher accumulated abnormal turnover ( $AT_{it+5}$ ) and a lower

Amihud illiquidity ratio ( $\lambda$ ). These results demonstrate that manipulators attract the participation of other investors in the market, as in Aggarwal and Wu (2006). For comparison, our estimation results, shown in column (1), indicate that abnormal turnover of manipulated stocks is higher than non-manipulated stocks by 141.6% on the day of manipulation; whereas, Huang and Cheng (2015) find that turnover of manipulated stocks is higher than non-manipulated stocks by 5.87% on average. Overall, our findings confirm our contention that manipulation increases trading activities both during and after manipulation, and thus Hypothesis 2 is confirmed.

[Insert Table 4 here]

#### 4.1.3 Stock price volatility and inflow of retail investors

Mean difference tests in Appendix D suggest that the volatility of manipulated stocks is significantly higher than that of control group stocks after manipulation. The idiosyncratic volatility of manipulated stocks is specified below.

(10)

where the dependent variable  $\sigma_{it}$  represents the 5-day idiosyncratic volatility after manipulation. The key independent variable,  $\text{Manipulated}_{it}$ , is equal to 1 if the stock is manipulated, and 0 otherwise.  $\text{Control}_{it}$  comprises various control variables that may affect stock price volatility. Following prior studies (Chakraborty and Yilmaz, 2004; Khwaja and Mian, 2005; Jiang et al., 2005; Comerton-Forde and Putniņš, 2011, 2014; Lee et al., 2013; Brandt et al., 2010; Foucault et al., 2011; Banerjee and Green, 2015; Neupane et al., 2017), we control for price ( $P_{it}$ ), past turnover ( $\text{Turnover}_{it}$ ), intraday volatility ( $\text{IntradayVol}_{it}$ ), past stock return volatility ( $\text{ReturnVol}_{it}$ ), absolute stock return ( $\text{AbsReturn}_{it}$ ), past illiquidity index ( $\text{Illiquidity}_{it}$ ), the company's size ( $\text{Size}_{it}$ ), the percentage of institutional stockholdings ( $\text{InstHldg}_{it}$ ), the number of analysts following ( $\text{Analysts}_{it}$ ), the market-to-book ratio ( $\text{MtoB}_{it}$ ), return on assets ( $\text{ROA}_{it}$ ), and Tobin's Q ratio ( $\text{Q}_{it}$ ).  $\epsilon_{it}$  is the error term.

Column (1) and column (5) in Table 5 present the estimation results of Model (10). These show that in comparison to control group stocks, the idiosyncratic volatility of manipulated stocks is significantly higher by 2.2% and 0.8% based on direct and indirect evidence, which is in line with the findings presented in Huang and Cheng (2015), Aggarwal and Wu (2006) and Hillion and Suominen (2004). For comparison, Huang and Cheng (2015) find that stock price volatility of manipulated stocks is higher than non-manipulated stocks by 3.05% on average.

Furthermore, studies establish that noise traders add to price volatility (Foucault et al., 2011; Banerjee and Green, 2015). Individual investors comprise a large proportion of the

Chinese stock market, and their trading behaviors are more susceptible to the influence of information unrelated to fundamentals. Consistent with Brandt et al. (2010), Foucault et al. (2011) and Choi et al. (2018), we expect that individual investors act as noise traders and that such retail trading will increase price volatility. To examine the hypothesis that opening price manipulation indirectly increases stock price volatility by attracting retail investors, Models (11), (12) and (13) are used to estimate the mediating effect of the net inflow ratio of retail trading.

(11)

(12)

(13)

where the dependent variable represents the 5-day cumulative net inflow of retail investors after manipulation. represents the 5-day idiosyncratic volatility after manipulation. The key independent variable is equal to 1 if the stock is manipulated, and 0 otherwise. comprises various control variables that may affect stock price volatility and the inflow of retail investors. Following prior studies (Brandt et al. , 2010; Foucault et al., 2011; Banerjee and Green, 2015; Neupane et al., 2017), we control for price (), past turnover(), intraday volatility(), past stock return volatility(), absolute stock return(), past illiquidity index(), the company’s size (), the percentage of institutional stockholdings (), the number of analysts following (), the market-to-book ratio (), return on assets (), and Tobin’s Q ratio (). is the error term.

The results in columns (2) and (6) of Table 5 show that after opening price manipulation, the net inflow ratio of retail trading for manipulated stocks is significantly higher than that of control group stocks by 6.4% and 1.0%, respectively, as indicated by direct and indirect evidence. The results in columns (3) and (7) report that the participation of retail investors increases volatility, and that on average, when the net inflow ratio of retail trading increases by 1%, stock price volatility increases by 3.1% and 7.8%, respectively, as indicated by direct and indirect evidence. The results in columns (4) and (8) show that, after factoring in both opening price manipulation () and the net inflow ratio of retail trading, the stock price volatility for manipulated stocks is higher by 1.7% and 0.9%, respectively, as indicated by direct and indirect evidence. These results indicate that opening price manipulation attracts an influx of retail investors into the market, which subsequently increases idiosyncratic volatility, providing strong support for Hypothesis 3.

[Insert Table 5 here]

## **4.2 External supervision, internal governance and mispricing**

### **4.2.1 External supervision and mispricing**

Information intermediaries, such as securities analysts and external auditors, undertake private information production that has the potential to inform investors, monitor managerial behavior, and facilitate the detection and discipline of market manipulation (Francis et al., 2013; Charitou et al., 2019; Gu et al., 2019). Therefore, we expect that stocks with stronger external supervision will have a lower degree of mispricing due to opening price manipulation. To test the hypothesis, we use two indicators to measure external supervision, with the first being analyst following. Analysts' earnings forecasts contain a wealth of fundamental information, and analyst following can help reduce information asymmetry in respect of listed companies and increase information transparency (Charitou et al., 2019; Gu et al., 2019). The second indicator is when one of the four major accounting firms (PricewaterhouseCoopers (PwC), Deloitte (DTT), KPMG (KPMG) and Ernst and Young (EY)) audits a company. Audit results issued by large accounting firms are more credible and can provide an assurance of stronger external supervision (Francis et al., 2013). For example, DeFond et al. (2017) find the "Big N effect" that the audit reports of the Big Four accounting firms are of higher quality than those of other practices. We divide the sample into two sub-samples: 1) based on whether the number of analysts following is higher than the industry median for the year; and 2) whether the auditors are a Big Four accounting firm. Table 6 reports the estimation results of Models (4) and (5) based on direct and indirect evidence, respectively. The estimation results presented in columns (1) to (4) indicate that market manipulation has a more significant negative effect on the 5-day CAR and positive effect on price reversal in the sub-samples of firms with low analyst attention than those with high analyst attention. Further, columns (5) to (8) present the results that the impacts of manipulation on the 5-day CAR and price reversal are significantly stronger for firms audited by non-Big-Four accounting firms. These results establish the crucial importance of strong external monitoring in mitigating the impact of manipulation on pricing accuracy.

[Insert Table 6 here]

### **4.2.2 Internal governance and mispricing**

Stocks with weak corporate governance are often characterized by low liquidity and a high degree of information asymmetry (Jiang et al., 2015; Liu et al., 2015), which encourages price manipulation. Prior literature suggests that stocks with poor corporate governance are easily manipulated and that the costs of manipulation are lower, because investors cannot distinguish

the information implicit in stock price fluctuations (Lee et al., 2013; Comerton-Forde and Putniņš, 2014; Huang and Cheng, 2015). Thus, we expect that stocks with stronger internal governance will have a lower degree of mispricing as a consequence of opening price manipulation.

To test the hypothesis above, we use two indicators to measure internal governance, with the first being the proportion of state-owned shares. State-owned enterprises are known to be less efficient in respect of internal governance and information transparency than their privately controlled counterparts due to serious agency problems (Liu et al., 2015). On the one hand, state-owned enterprises usually have lower operating efficiency, since government ownership shields them from market competition and market discipline (Chen et al., 2011). On the other hand, top executives of state-owned enterprises are usually appointed by the government, and thus they comply with government agendas in achieving certain social and fiscal goals rather than maximizing shareholders' value (Jiang and Kim, 2020). We divide the sample into two sub-samples based on whether the company is a state-owned enterprise. The estimation results of Models (4) and (5), shown in columns (1) to (4) of Table 7, indicate that the effect of manipulation is significantly stronger for state-owned firms than for non-state-owned firms. However, since a high proportion of state-owned enterprises are large companies, it might be argued that the positive relationship between state ownership and firm size<sup>9</sup> could bias the estimation results. To address this concern, we further conduct an independent double sort on firm size (Small, Median and Large) and state ownership (Low and High). Thus, we divide the sample into six sub-samples, which are 1) Small-size and Low-state-ownership; 2) Small-size and High-state-ownership; 3) Median-size and Low-state-ownership; 4) Median-size and High-state-ownership; 5) Large-size and Low-state-ownership; 6) Large-size and High-state-ownership. We investigate the impact of manipulation on pricing accuracy in six sub-samples, and the empirical results in Appendix E confirm that the impact of manipulation is stronger in sub-samples of Small-High, Median-High, and Big-High than in sub-samples of Small-Low, Median-Low, and Big-Low. These results lead us to conclude that firms with higher state ownership have a larger degree of mispricing unrelated to size.

The second indicator of internal governance is the presence of independent directors. Research suggests that independent directors play an active role in supervising listed companies in China and improve information transparency (Liu et al., 2015; Jiang et al., 2015). Thus, we

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<sup>9</sup> In the sample of direct (indirect) evidence, state-owned enterprises account for 43.03% (43.81%), and the average firm size is 21.10 (23.03), while non-state-owned enterprises account for 56.97% (56.19%), with an average firm size of 20.56 (22.53). The difference between the firm sizes of the two groups is 0.54 (0.50), and the t-statistical value is 1.67 (7.32).

divide the sample into two sub-samples based on whether the proportion of independent directors on the board is higher than the industry median. The estimation results presented in columns (5) to (8) of Table 7 indicate that market manipulation has a more significant, negative effect on 5-day CAR and positive effect on price reversal for firms with a lower proportion of independent directors on a board, in comparison to firms with a higher proportion of independent directors. These results indicate that stocks with strong internal governance have a lower degree of mispricing, which provides strong support for Hypothesis 4.

[Insert Table 7 here]

### **4.3 Robustness test**

#### **4.3.1 Propensity score matching (PSM)**

Despite our results consistently demonstrating the impact of manipulation on pricing accuracy, trading activity and stock volatility, it could be argued that the selection of stocks is not random, and that manipulators often choose stocks with specific characteristics. To address the issue of selection bias and endogeneity in the baseline results, we apply a propensity score matching (PSM) analysis to address selection bias arising from firm-related characteristics and bias related to functional misspecification (Roberts and Whited, 2013). We use a Probit specification to estimate the probabilities of being manipulated ( $\theta$ ) on a comprehensive list of observable characteristics, including all the control variables in our baseline model. We then use the propensity scores from this Probit estimation and perform the matching. To ensure that our treated and control firms are comparable, we match treatment and control firms using propensity score matching, based on 1-to-1 matching with replacement matching. Then, we estimate Models (4) and (5) with the manipulated group and the matched stocks in the control group. The results reported in Appendix F indicate that manipulation decreases stock returns and increases trading activity and stock volatility across all models. These findings are consistent with our baseline results and confirm the robustness of our findings.

#### **4.3.2 Alternative overnight returns**

In our construction of the manipulation identification model, abnormal overnight gap is one of the important conditions to detect manipulation. However, Qiao and Dam (2020) find that the overnight return is significantly negative in China due to the “T+1” trading rules, and thus some large buyers may require a discount to purchase the stock during the next trading day. To address the issue, we make use of an alternative method of measuring overnight returns following Akbas et al. (2021), in which the previous overnight return is imputed from daytime returns and the daily close-to-close returns<sup>10</sup>. The results are reported in Appendix G. The



results show that the alternative method of overnight return generates the result, which is consistent with the previous findings, providing evidence to support our contention that our baseline results are not driven by the “T+1” trading rules.

### **4.3.3 Stock market environment: Bear vs. bull market period**

Investor behavior differs significantly in bull and bear market periods (Demirer and Kutan, 2006). Therefore we examine whether the effects of market manipulation remain robust during such periods. Following Chen (2009), we divide the sample period into the bear market period and the bull market period, based on whether the average market return in the past 5 months is greater than 0. Appendix H shows the distributions for the bull as well as bear market periods. From 2007 to 2017, there were 74 bull market months and 58 bear market months, accounting for 56.06 and 43.94% of the trading periods, respectively. There are 87 cases of opening price manipulation reported by the CSRC, of which 58 cases, or 66.67%, occur during the bull market period, and 29 cases, or 33.33%, that occur during the bear market period. Similarly, of the 19,003 suspected cases detected by our opening price manipulation identification model, 10,980 occur in the bull market period, accounting for 57.78%, and 8,023 occur in the bear market period, accounting for 42.22%. The estimation results are reported in Appendix I, showing that our baseline results continue to hold for both bull and bear markets.

Furthermore, the market witnessed some spectacular fluctuations around the middle of the sample period. For example, the 2007-2008 financial crisis, which impacted global financial markets, and the 2014-2015 stock market bubble in China, have a significant impact on stock price performance and market liquidity during our sample period. Accordingly, we examine the robustness of our findings during these two periods. Following Cumming et al. (2020) and Han and Liang (2017), we define the period from August 2007 to December 2008, and the period from June 2015 to September 2015, as Chinese stock market crash periods. In addition, we define the periods from January 2007 to July 2007 and July 2014 to June 2015 as Chinese stock market bubble periods. We re-run our main tests over these two sub-samples, reporting the results in Appendix J. They clearly indicate that our baseline results continue to hold across these two periods, demonstrating the robustness of our findings on the impact of manipulation on mispricing, trading activity and price volatility.

### **4.3.4 Adjusting for risk factors**

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<sup>10</sup> Specifically, following Akbas et al. (2021), for each firm  $i$  on day  $t$ , we define the daytime (open-to-close) return as the relative price change from the market open to the close on day  $t$ ,  $r_{i,t}^{daytime}$ . We then impute the previous overnight (close-to-open) return from the daytime return and the daily close-to-close return  $r_{i,t}^{close-to-close}$ , as  $r_{i,t}^{overnight} = r_{i,t}^{close-to-close} - r_{i,t}^{daytime}$ .

To establish the robustness of our results even further, we re-estimate our baseline models by applying three risk adjustments based on market risk factors, including the Fama-French three factor model (FF3F), the Carhart four factor model (Carhart) and the Fama-French five factor model (FF5F). The results are presented in the Appendix K. After risk factor adjustments, performance of manipulated stocks is significantly weaker than that of control group stocks, which further confirms the robustness of our conclusions.

#### **4.3.5 Different time windows**

Next, we conduct analyses on different time windows. We adopt the time window of 10 and 20 trading days after manipulation to examine the influence of opening price manipulation on mispricing. The estimation results are presented in Appendix L. Columns (1) and (5) report the influence of manipulation on 10-day cumulative abnormal returns. Columns (2) and (6) report the influence of manipulation on the probability of price reversal 10 trading days after manipulation. Similarly, Columns (3) and (7) report the influence of manipulation on the 20-day cumulative abnormal returns. Columns (4) and (8) report the influence of manipulation on the probability of price reversal 20 trading days after manipulation. The overall results confirm that our findings remain robust even when computed in different time windows.

#### **4.3.6 Control group selection**

To confirm the robustness of the conclusion, a variety of control groups are constructed and incorporated for comparison with the manipulated group. We carry out the matching procedure based on firm size, previous stock returns, and industry type, and re-run the main empirical tests, reporting the estimated results in Appendix M. In Panel A and Panel B, we form 10 portfolios by sorting on size, and match each manipulated stock with stocks in the same size-decile portfolios. In Panel C and Panel D, we match each manipulated stock with non-manipulated stocks displaying similar daily returns on the previous trading day<sup>11</sup>. In Panel E and Panel F, we match each manipulated stock with non-manipulated stocks in the same industry. These results show that manipulation decreases stock returns and increases trading activity and stock volatility across all samples, which provides consistent support for the robustness of our findings.

## **5 Conclusion**

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<sup>11</sup> To be more specific, we calculate the daily returns on the previous trading day and round them to the nearest hundredth, and chooses non-manipulated stocks displaying the same daily returns on the previous trading day as the control group.

A call auction is a mechanism most commonly adopted by stock exchanges across the world to determine the opening price of a security. Major stock exchanges utilizing this process include the NYSE (New York Stock Exchange), the NASDAQ Stock Exchange and the LSE (London Stock Exchange). Moreover, it is common practice for most stock exchanges to allow investors to cancel orders during the pre-opening session, such as on the Australian Stock Exchange (Comerton-Forde and Rydge, 2006b) and the London Stock Exchange (Ibikunle, 2015), which facilitates opening price manipulation. However, academia has so far failed to investigate opening price manipulation, creating a significant research lacuna. Based on both direct evidence, consisting of 87 opening price manipulation cases disclosed by the China Securities Regulatory Commission (CSRC); and indirect evidence, comprising 19,003 suspected cases detected by an identification model of opening price manipulation, our study examines the impact of manipulation on mispricing, investors' losses, market trading activity and price volatility, and evaluates the economic consequences.

Four major findings emerge from our analyses. First, this trading malpractice leads to manipulated stocks opening with a price that is higher than their fundamental value. Such distorted stock prices will be gradually corrected on the manipulation day as well as on following trading days. However, in comparison to control group stocks, manipulated stocks have a lower cumulative abnormal return after manipulation, and the probability of price reversal is significantly higher. Therefore, investors who buy manipulated stocks, either at their opening price or volume-weighted average price on a manipulation day, suffer investment losses. Second, manipulation increases trading activity for manipulated stocks both on manipulation day and on the days following manipulation. Third, manipulation attracts an influx of retail investors, which increases price volatility. Further, our study demonstrates that enhancing the intensity of external supervision and internal governance can reduce the degree of mispricing caused by opening price manipulation. Stocks with strong external supervision, such as those with high analyst attention, and those of firms audited by the Big Four accounting practices, will have a lower degree of mispricing due to opening price manipulation. Similarly, stocks with strong corporate governance, such as those of non-state-owned enterprises, and those of firms with a high proportion of independent directors on their boards, will have a lower degree of mispricing due to opening price manipulation.

Our study makes valuable contributions to the growing academic literature on market misconduct. Mispricing and investor losses caused by market manipulation have received widespread attention from academia, market regulators and investors in recent years. Putniņš (2012) observes that gathering evidence from a comprehensive sample of manipulation cases is

essential to analyze systematically the influences and mechanisms of market manipulation. Therefore, by examining manipulation cases disclosed by the CSRC and constructing a manipulation identification model, we significantly augment empirical evidence on market manipulation and make significant contributions to research by identifying the causes and effects of opening price manipulation.

Further, our timely study provides policy insights to regulators seeking to curb market misconduct. In highlighting the vulnerability of worldwide markets to such systematic abuse, our findings indicate the urgent need for protecting retail investors and improving market quality. To counter the inimical influence that opening price manipulation has on the efficiency of asset pricing and the interests of investors, stock market supervisory bodies must construct and perfect an opening price manipulation detection and warning system to strengthen regulatory control. They should also increase the severity of punishments for stock price manipulation to deter potential offenders. In particular, enhancing the intensity of external supervision and internal governance would be effective for mitigating the degree of mispricing caused by opening price manipulation, and helping to maintain the market's fairness and efficiency, protect retail investors, and improve market quality.

Moreover, given that the pre-opening call auction mechanisms adopted by stock exchanges throughout the world are similar in their functioning, our findings, albeit derived in the context of China, can be readily generalized to other markets. We suggest that further research be undertaken to extend our understanding of opening price manipulation. For example, if and how call auction matching algorithms and order-balancing mechanisms can reduce manipulation are among important questions for theoreticians to answer. We readily concede that the identification model has its limitations, and propose using a more sophisticated design to improve the success rate of the opening price manipulation identification model in future research. Similarly, more detailed explorations of investor behavior and more accurate estimates of traders' losses using investor account data are to be encouraged. Furthermore, an investigation is needed to determine effective supervisory processes for reducing manipulation and mitigating its impact on efficient markets, which is a question of acute concern in the context of global trading.

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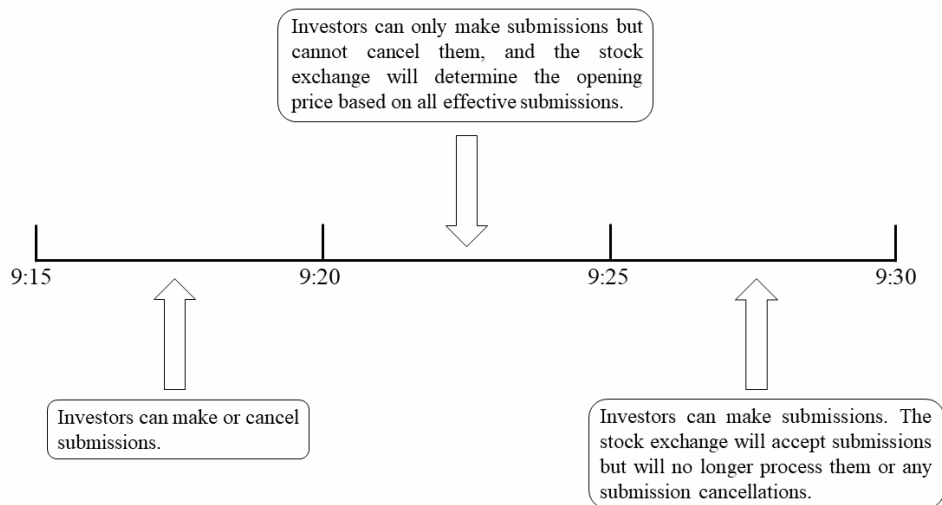
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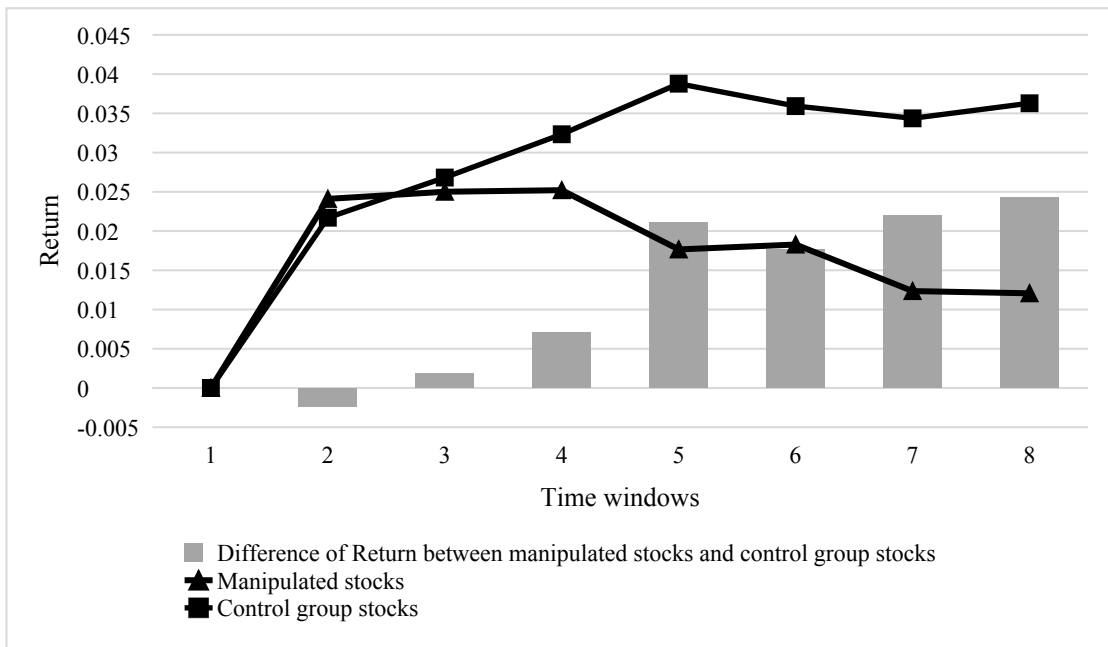
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**Figure 1. The rule of pre-opening call auction in Chinese stock market**

Notes: Figure 1 reports the trading rules of pre-opening call auction on the Shanghai and Shenzhen Stock Exchanges. Between 9:15 and 9:25 a.m., investors can submit or cancel orders. Between 9:20 and 9:25 a.m., investors can only submit orders, and the stock exchange will determine the opening price based on all effective submissions made before 9:25 a.m. Between 9:25 to 9:30 a.m., the stock exchange will not process any order submissions or cancellations. And at 9:30, the stock exchange opens for continuous auction.



**Figure 2. Short-term Price Performance for Manipulated Stocks and Control Group Stocks**

Notes: Figure 2 compares cumulative return for manipulated stocks against that of control group stocks. The x-axis is the time window, and the y-axis is the cumulative stock return. And the day of manipulation (T+0) is further divided into pre-opening call auction (T+0 Opn) and continuous auction after the market opens (T+0 CIs).

**Table 1. Descriptive Statistics for Main Variables**

variable	N	mean	sd	min	p25	p50	p75	max
Panel A: Direct Evidence								
Dum_manip	23330	0.004	0.061	0	0	0	0	1
Intra_ret[0]	23330	0.001	0.025	-0.145	-0.010	-0.000	0.011	0.163
CAR[1, 5]	23330	0.009	0.060	-0.405	-0.022	0.003	0.035	0.499
Reverse	23330	0.394	0.489	0	0	0	1	1
AT[0]	23330	-0.022	0.842	-0.974	-0.565	-0.250	0.257	13.616
CAT[1, 5]	23330	-0.009	3.644	-4.769	-2.478	-0.956	1.459	63.712
Amihud[0]	23330	38.499	71.485	0.000	5.538	16.034	41.160	331.89
Amihud[1, 5]	23330	20.996	44.690	0.000	2.801	8.451	21.763	190.439
Idivol[1, 5]	23330	0.017	0.012	0.001	0.008	0.014	0.022	0.105
CNI_retail[1, 5]	17468	-0.014	0.091	-0.503	-0.064	-0.021	0.021	0.811
Price	23330	2.612	0.692	0.315	2.138	2.589	3.056	5.855
Lagturnover	23330	0.034	0.039	0.000	0.010	0.021	0.044	0.755
Intravol	23330	15.330	27.922	0.000	3.276	6.112	13.691	66.468
Lagvol	23330	0.029	0.022	0.000	0.015	0.024	0.039	0.085
Absret	23330	0.022	0.025	0.000	0.006	0.013	0.028	0.102
LagAmihud5	23330	0.016	0.715	0.000	0.001	0.002	0.006	0.070
Size	23330	20.794	1.211	16.992	20.028	20.606	21.335	25.070
Inst	23330	0.055	0.059	0.000	0.016	0.039	0.076	0.847
Follow	23330	2.954	3.984	0	0	1	4	37
Mtb	23330	0.503	0.258	0.071	0.295	0.467	0.687	1.122
Roa	23330	0.027	0.041	-0.683	0.006	0.018	0.042	0.494
Tobinq	23330	2.592	8.693	0.041	0.913	1.725	3.056	969.796
Panle B: Indirect Evidence								
Dum_manip	1172987	0.001	0.036	0	0.	0	0	1
Intra_ret[0]	1172987	0.012	0.034	-0.342	-0.006	0.011	0.030	0.256
CAR[1, 5]	1172987	0.000	0.064	-0.838	-0.033	-0.006	0.026	3.479
Reverse	1172987	0.425	0.494	0.000	0.000	0.000	1.000	1.000
AT[0]	1172987	-0.048	4.781	-1.000	-0.604	-0.347	0.104	3.230
CAT[1, 5]	1172987	-0.169	9.701	-4.996	-2.762	-1.430	0.828	15.534
Amihud[0]	1172987	0.011	0.382	0.000	0.001	0.003	0.007	0.043
Amihud[1, 5]	1172987	0.003	0.059	0.000	0.000	0.001	0.003	0.033
Idivol[1, 5]	1172987	0.038	0.766	0.000	0.010	0.016	0.025	254.308
CNI_retail[1, 5]	971081	0.008	0.184	-1.000	-0.088	0.005	0.092	1.000
Price	1172987	2.451	0.737	-1.966	1.962	2.420	2.915	6.641
Lagturnover	1172987	0.031	0.039	0.000	0.009	0.019	0.038	0.795
Intravol	1172987	14.646	18.779	0.000	4.597	8.882	17.609	3,423.822
Lagvol	1172987	0.033	0.038	0.000	0.019	0.028	0.043	9.248
Absret	1172987	0.029	0.026	0.000	0.010	0.021	0.040	1.034
LagAmihud5	1172987	0.034	1.427	0.000	0.001	0.004	0.010	908.529
Size	1172987	22.767	1.282	19.049	21.922	22.600	23.375	30.936
Inst	1172987	6.845	8.737	0.000	0.720	3.628	9.676	75.104
Follow	1172987	14.007	20.126	0	1	6	19	252
Mtb	1172987	0.604	0.245	0.107	0.412	0.607	0.803	1.107
Roa	1172987	0.036	0.062	-0.268	0.013	0.035	0.065	0.197
Tobinq	1172987	2.132	1.447	0.903	1.245	1.649	2.427	9.314
Panel C: Mean Difference Test								
Variable Name	Mean(M Group)	Mean(C Group)	Difference(M-C)	Standard Deviation	t statistic	P statistic		
Size	20.057	20.797	-0.074	0.031	-2.365	0.018**		

Inst	0.052	0.055	-0.003	0.006	-0.428	0.669
Follow	2.163	2.957	-0.794	0.430	-1.844	0.065*
Mtb	0.488	0.503	-0.015	0.028	-0.531	0.595
Roa	0.023	0.026	-0.004	0.004	-0.893	0.371
Tobinq	3.178	2.589	0.589	0.939	0.627	0.531

Notes: In Table 1, panel A and panel B provide descriptive statistics for main independent variables, main dependent variables and control variables. It is worth pointing out that RESSET Database began to disclose the direction of capital flow of retail trading in 2012. Thus, the sample size of cumulative net inflow of retail trading () is only 17468 and 971081. Panel C reports results of the mean difference test to compare manipulated stocks against control group stocks in terms of fundamental characteristics. \*, \*\*, and \*\*\* denote 10%, 5%, and 1% levels of statistical significance, respectively. Detailed definitions of variables are shown in Appendix B.

**Table 2. Opening Price Manipulation and Stock Price Performance**

VARIABLES	Direct Evidence			Indirect Evidence		
	(1) Intra ret[0]	(2) CAR[1, 5]	(3) Reverse	(4) Intra ret[0]	(5) CAR[1, 5]	(6) Reverse
Dum_manip	0.005 (0.006)	-0.021*** (0.006)	0.403*** (0.106)	-0.061*** (0.001)	-0.010*** (0.002)	1.001*** (0.140)
Price	-0.001* (0.000)	-0.004*** (0.001)	0.176*** (0.011)	-0.003*** (0.000)	-0.003*** (0.000)	0.078*** (0.010)
Lagturnover	0.192*** (0.008)	-0.148*** (0.014)	-0.022 (0.177)	0.152*** (0.002)	-0.121*** (0.003)	2.256*** (0.184)
Intravol	-0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)	0.004*** (0.001)
Lagvol	-0.023*** (0.009)	0.205*** (0.039)	0.809*** (0.311)	0.022*** (0.004)	0.034*** (0.008)	-12.300*** (0.543)
Size	-0.004*** (0.000)	0.005*** (0.000)	0.005 (0.009)	0.000*** (0.000)	-0.000*** (0.000)	0.041*** (0.008)
Inst	-0.000 (0.000)	0.000*** (0.000)	-0.004*** (0.001)	0.000*** (0.000)	0.000** (0.000)	0.002** (0.001)
Follow	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000*** (0.000)	-0.000*** (0.000)	-0.000 (0.000)
Mtb	0.006*** (0.001)	-0.026*** (0.002)	0.164*** (0.049)	-0.006*** (0.000)	-0.019*** (0.001)	0.069 (0.050)
Roa	0.004 (0.003)	0.015** (0.006)	-0.380*** (0.123)	0.009*** (0.001)	0.026*** (0.001)	-0.658*** (0.093)
Tobinq	0.001*** (0.000)	-0.002*** (0.000)	0.013** (0.006)	-0.000*** (0.000)	-0.000** (0.000)	0.013 (0.009)
Constant	-0.008* (0.005)	0.072*** (0.008)	-2.328*** (0.184)	0.001 (0.001)	0.026*** (0.002)	-1.506*** (0.186)
Observations	23,330	23,330	23,330	1,172,987	1,172,987	1,172,987
R-squared	1.186	0.044		0.057	0.014	
Pseudo R2			0.068			0.039
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Notes: Table 2 reports the estimation of Model (3), Model (4) and Model (5). Columns (1) - (3) report results based on direct evidence, and columns (4) - (6) report results based on indirect evidence. The dependent variable in column (1) and column (4) are intraday abnormal return ( $\Delta$ ), the dependent variable in column (2) and column (5) are cumulative abnormal return ( $\Delta$ ), and the dependent variable in column (3) and column (6) are price reversal ( $\Delta$ ). All regressions include year fixed effects and industry fixed effects. \*, \*\*, and \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively. Detailed definitions of variables are shown in Appendix B.

**Table 3. Opening Price Manipulation and Investors' Losses**

	(1)	(2)	(3)	(4)	(5)	(6)
	Opnprc (pre-opening call auction)			VWAP (all day)		
Time Frame	T+0	T+3	T+5	T+0	T+3	T+5
Trading Price RMB/Share	21.78	21.11	20.88	21.81	21.11	20.88
Position Value In Millions	7.92	7.68	7.59	93.88	90.87	89.88
Investors' Losses In Millions	-	0.24	0.33	-	3.01	4
Investors' Losses Percentage	-	3.08%	4.13%	-	3.21%	4.26%

Notes: Table 3 reports the effect of manipulation on investor benefits. Columns (1) and (4) list respectively the average purchase price of investors during pre-opening call auction on manipulation day () and the average purchase price for those who buy shares of the manipulated stock at any given time on manipulation day (), as well as the corresponding position value. The hypothetical average purchase price is then compared with the closing price on the third and fifth day after manipulation () to estimate the losses incurred by investors. Investors' losses are estimated both as an amount and as a percentage. Columns (2) and (3) report the investor loss () calculated with the opening price on manipulation day as the hypothetical average purchase price, and columns (5) and (6) report the investor loss (Investors' loss2) calculated with the volume-weighted average price on manipulation day as the hypothetical average purchase price. Detailed definitions of variables are shown in Appendix B.



**Table 4. Opening Price Manipulation and Trading Activity**

VARIABLES	Direct Evidence				Indirect Evidence			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AT[0]	Amihud[0]	CAT[1,5]	Amihud[1,5]	AT[0]	Amihud[0]	CAT[1,5]	Amihud[1,5]
Dum_manip	1.416*** (0.215)	-10.734* (6.007)	3.545*** (1.011)	-12.112*** (1.141)	0.268*** (0.056)	-0.414*** (0.059)	0.790*** (0.128)	-0.670*** (0.125)
Price	-0.248*** (0.047)	0.006*** (0.001)	-0.237* (0.137)	0.002*** (0.000)	-0.318*** (0.015)	0.022*** (0.002)	-0.170*** (0.025)	0.005*** (0.000)
Lagturnover	28.874*** (8.894)	-0.569*** (0.121)	3.933 (4.841)	-0.101*** (0.037)	31.485*** (1.637)	-1.370*** (0.059)	17.606*** (0.783)	-0.317*** (0.019)
Intravol	-0.001 (0.002)	-0.001*** (0.000)	-0.026*** (0.004)	-0.000* (0.000)	0.004** (0.002)	-0.001*** (0.000)	-0.013*** (0.001)	-0.000*** (0.000)
Lagvol	-10.574** (5.187)	1.752*** (0.574)	29.087** (11.398)	0.268* (0.138)	-2.984*** (0.585)	1.152*** (0.207)	3.770*** (0.810)	0.286*** (0.055)
Absret	4.951*** (1.644)	0.888*** (0.161)	55.936*** (9.200)	0.118** (0.051)	2.189*** (0.474)	2.216*** (0.085)	49.065*** (1.226)	0.401*** (0.027)
Size	0.162*** (0.037)	-0.005*** (0.001)	0.063 (0.039)	-0.002*** (0.000)	0.159*** (0.009)	-0.015*** (0.001)	0.070*** (0.011)	-0.004*** (0.000)
Inst	0.011*** (0.004)	-0.000*** (0.000)	-0.014*** (0.005)	-0.000*** (0.000)	0.013*** (0.001)	-0.001*** (0.000)	0.001 (0.001)	-0.000*** (0.000)
Follow	0.001** (0.000)	-0.000*** (0.000)	-0.004* (0.002)	-0.000** (0.000)	0.001*** (0.000)	-0.000*** (0.000)	-0.003*** (0.000)	-0.000*** (0.000)
Mtb	-0.255*** (0.094)	0.012*** (0.003)	-0.796*** (0.194)	0.004*** (0.001)	-0.190*** (0.026)	-0.021*** (0.005)	-0.920*** (0.053)	-0.007*** (0.001)
Roa	0.037 (0.399)	0.084*** (0.020)	0.808 (0.730)	0.016*** (0.006)	0.684*** (0.062)	0.109*** (0.016)	1.080*** (0.106)	0.027*** (0.003)
Tobinq	0.017*** (0.004)	-0.001** (0.001)	-0.055** (0.027)	-0.000 (0.000)	0.020*** (0.002)	-0.002* (0.001)	-0.038*** (0.007)	-0.001*** (0.000)
Constant	-4.170*** (1.046)	0.071*** (0.020)	-0.536 (0.856)	0.030*** (0.005)	-4.521*** (0.240)	0.290*** (0.018)	-3.411*** (0.236)	0.085*** (0.004)
Observations	23,330	23,330	23,330	23,330	1,172,987	1,172,987	1,172,987	1,172,987
R-squared	0.021	0.063	0.045	0.025	0.060	0.042	0.044	0.023
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Table 4 reports the estimation of Model (6), Model (7), Model (8) and Model (9). Columns (1) - (4) report results based on direct evidence, and columns (5) - (8)



report results based on indirect evidence. The dependent variable in column (1) and column (5) is abnormal turnover on the manipulation day ( $\Delta$ ), the dependent variable in column (2) and column (6) is cumulative abnormal turnover after manipulation ( $\Delta$ ), the dependent variable in column (3) and column (7) is Amihud ratio on the manipulation day ( $\Delta$ ), and the dependent variable in column (4) and column (8) is Amihud ratio for 5 trading days after manipulation ( $\Delta$ ). All regressions include year fixed effects and industry fixed effects. \*, \*\*, and \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively. Detailed definitions of variables are shown in Appendix B.



**Table 5. Opening Price Manipulation and Volatility**

VARIABLES	Direct Evidence				Indirect Evidence			
	(1) Idivol[1, 5]	(2) CNI_retail[1, 5]	(3) Idivol[1, 5]	(4) Idivol[1, 5]	(5) Idivol[1, 5]	(6) CNI_retail[1, 5]	(7) Idivol[1, 5]	(8) Idivol[1, 5]
Dum_manip	0.022*** (0.001)	0.064*** (0.020)		0.017*** (0.001)	0.008*** (0.002)	0.010*** (0.004)		0.009*** (0.002)
CNI_retail[1, 5]			0.031** (0.016)	0.031** (0.016)			0.078*** (0.019)	0.078*** (0.019)
Price	0.013 (0.015)	-0.014*** (0.001)	0.012 (0.016)	0.013 (0.018)	0.023*** (0.004)	-0.006*** (0.000)	0.031*** (0.005)	0.031*** (0.005)
Lagturnover	0.344 (0.831)	0.242*** (0.022)	0.540 (0.880)	0.382 (0.923)	0.264*** (0.088)	0.198*** (0.007)	0.189* (0.104)	0.189* (0.104)
Intravol	0.003*** (0.000)	-0.000*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	-0.000 (0.000)	-0.001*** (0.000)	0.000 (0.000)	0.000 (0.000)
Lagvol	-1.866* (0.968)	-0.371*** (0.043)	-1.933* (1.033)	-2.022* (1.075)	-0.554*** (0.107)	0.047*** (0.011)	-0.628*** (0.133)	-0.628*** (0.133)
Absret	2.080*** (0.427)	1.657*** (0.044)	2.250*** (0.423)	2.244*** (0.420)	1.373*** (0.083)	2.163*** (0.015)	1.045*** (0.073)	1.045*** (0.073)
LagAmihud5	0.028 (0.026)	0.011** (0.004)	0.027 (0.026)	0.027 (0.026)	0.044** (0.018)	0.007*** (0.002)	0.042** (0.017)	0.042** (0.017)
Size	0.004 (0.006)	0.007*** (0.001)	0.006 (0.007)	0.005 (0.007)	0.003*** (0.001)	0.006*** (0.000)	0.003*** (0.001)	0.003*** (0.001)
Inst	0.000 (0.001)	0.000 (0.000)	0.000 (0.001)	0.000 (0.001)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000** (0.000)	-0.000** (0.000)
Follow	-0.000** (0.000)	0.000** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Mtb	0.063 (0.039)	-0.012** (0.006)	0.066 (0.042)	0.065 (0.042)	0.025** (0.010)	-0.020*** (0.002)	0.037*** (0.012)	0.037*** (0.012)
Roa	0.011 (0.060)	-0.006 (0.015)	0.019 (0.064)	0.018 (0.064)	-0.043*** (0.009)	-0.018*** (0.004)	-0.037*** (0.011)	-0.037*** (0.011)
Tobinq	0.018*** (0.006)	0.001 (0.001)	0.020*** (0.007)	0.019*** (0.006)	0.011*** (0.002)	0.002*** (0.000)	0.011*** (0.003)	0.011*** (0.003)
Constant	-0.250* (0.137)	-0.168*** (0.022)	-0.293* (0.156)	-0.252* (0.140)	-0.169*** (0.027)	-0.208*** (0.006)	-0.144*** (0.030)	-0.144*** (0.030)
Observations	17,468	17,468	17,468	17,468	971,081	971,081	971,081	971,081

R-squared	0.028	0.088	0.123	0.129	0.017	0.113	0.021	0.021
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Table 5 reports the estimation of Model (10), Model (11), Model (12) and Model (13). Columns (1) - (4) report results based on direct evidence, and columns (5) - (8) report results based on indirect evidence. The dependent variable in column (1), (3) to (5), and (7) to (8) is idiosyncratic volatility ( $\sigma$ ). The dependent variable in column (2) and column (6) is net inflow ratio of retail trading ( $\beta$ ). All regressions include year fixed effects and industry fixed effects. \*, \*\*, and \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively. Detailed definitions of variables are shown in Appendix B.

**Table 6. External Supervision and Mispricing**

VARIABLES	Low-Analyst Attention		High-Analyst Attention		Non-Big-Four		Big-Four	
	(1) CAR[1, 5]	(2) Reverse	(3) CAR[1, 5]	(4) Reverse	(5) CAR[1, 5]	(6) Reverse	(7) CAR[1, 5]	8 Reverse
Panel A: Direct Evidence								
Dum_manip	-0.021*** (0.008)	0.592*** (0.225)	-0.022* (0.012)	0.061 (0.226)	-0.023*** (0.009)	0.374** (0.162)	-0.017 (0.011)	0.109 (0.657)
Price	-0.004*** (0.001)	0.197*** (0.015)	-0.007*** (0.001)	0.237*** (0.015)	-0.006*** (0.001)	0.227*** (0.011)	-0.008*** (0.002)	0.297*** (0.044)
Lagturnover	-0.168*** (0.018)	0.298 (0.238)	-0.120*** (0.022)	-0.662** (0.272)	-0.147*** (0.014)	-0.037 (0.183)	-0.163** (0.071)	-0.261 (0.875)
Intravol	0.000*** (0.000)	0.003*** (0.000)	0.000*** (0.000)	0.001* (0.000)	0.000*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	-0.003** (0.001)
Lagvol	0.217*** (0.043)	2.680*** (0.467)	0.138*** (0.049)	0.286 (0.409)	0.176*** (0.038)	1.833*** (0.349)	0.260** (0.108)	-4.461*** (1.436)
Size	-0.001*** (0.001)	0.056*** (0.012)	-0.002*** (0.000)	0.066*** (0.010)	-0.002*** (0.000)	0.071*** (0.009)	-0.001 (0.001)	0.047* (0.025)
Inst	0.000*** (0.000)	-0.004*** (0.001)	0.000*** (0.000)	-0.004*** (0.001)	0.000*** (0.000)	-0.005*** (0.001)	0.000 (0.000)	-0.004* (0.002)
Follow	0.001*** (0.000)	0.005 (0.003)	-0.000** (0.000)	0.001 (0.000)	0.000 (0.000)	-0.001 (0.000)	-0.000 (0.000)	0.000 (0.001)
Mtb	-0.013*** (0.003)	0.047 (0.064)	-0.018*** (0.004)	0.097 (0.078)	-0.014*** (0.002)	0.034 (0.050)	-0.012 (0.009)	0.560** (0.247)
Roa	0.020** (0.008)	-0.269* (0.157)	0.048*** (0.011)	-0.988*** (0.214)	0.036*** (0.007)	-0.629*** (0.126)	0.066** (0.027)	-1.725*** (0.651)
Tobinq	-0.001* (0.000)	0.008 (0.007)	-0.001** (0.001)	0.004 (0.011)	-0.001*** (0.000)	0.002 (0.006)	-0.005** (0.002)	0.175*** (0.057)
Constant	0.051*** (0.013)	-1.878*** (0.286)	0.065*** (0.012)	-1.967*** (0.258)	0.062*** (0.009)	-2.173*** (0.203)	0.022 (0.031)	-2.292** (1.088)
Observations	12,375	12,375	10,955	10,955	21,356	21,356	1,974	1,974
R-squared	0.030		0.042		0.032		0.066	
Pseudo R2		0.076		0.061		0.067		0.075
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Indirect Evidence								
Dum_manip	-0.010*** (0.002)	0.970*** (0.049)	-0.006*** (0.002)	0.618*** (0.024)	-0.012*** (0.002)	1.059*** (0.147)	-0.010** (0.005)	0.338 (0.532)
Price	-0.002*** (0.000)	0.194*** (0.003)	-0.005*** (0.000)	0.212*** (0.003)	-0.004*** (0.000)	0.077*** (0.010)	-0.005*** (0.000)	0.183*** (0.047)
Lagturnover	-0.151*** (0.004)	0.251*** (0.054)	-0.086*** (0.004)	-0.662*** (0.060)	-0.122*** (0.003)	2.330*** (0.188)	-0.138*** (0.016)	0.404 (1.209)
Intravol	-0.000*** (0.000)	0.003*** (0.000)	0.000 (0.000)	0.002*** (0.000)	-0.000*** (0.000)	0.003*** (0.001)	0.000*** (0.000)	0.011** (0.004)
Lagvol	0.052*** (0.013)	-0.602*** (0.175)	0.015** (0.007)	-0.286*** (0.105)	0.034*** (0.008)	-12.250*** (0.560)	0.012 (0.015)	-14.031*** (2.478)
Size	0.000*** (0.000)	0.022*** (0.003)	-0.001*** (0.000)	0.021*** (0.002)	-0.000 (0.000)	0.041*** (0.009)	-0.001*** (0.000)	-0.002 (0.026)
Inst	-0.000*** (0.000)	-0.001*** (0.000)	0.000** (0.000)	-0.002*** (0.000)	0.000* (0.000)	0.003*** (0.001)	0.000 (0.000)	0.001 (0.002)
Follow	0.000*** (0.000)	-0.008*** (0.001)	-0.000** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	0.000 (0.000)	0.001 (0.001)
Mtb	-0.019*** (0.001)	0.240*** (0.014)	-0.021*** (0.001)	0.368*** (0.017)	-0.019*** (0.001)	0.067 (0.052)	-0.022*** (0.002)	0.218 (0.220)
Roa	0.025*** (0.002)	-0.440*** (0.027)	0.012*** (0.002)	-0.529*** (0.044)	0.028*** (0.001)	-0.634*** (0.095)	0.010* (0.006)	-0.019 (0.876)
Tobinq	-0.000*** (0.000)	0.008*** (0.002)	0.000*** (0.000)	0.010*** (0.003)	-0.000* (0.000)	0.015 (0.009)	-0.001 (0.001)	-0.044 (0.038)
Constant	0.008*** (0.003)	-1.537*** (0.062)	0.044*** (0.003)	-1.621*** (0.054)	0.024*** (0.002)	-1.519*** (0.207)	0.099*** (0.019)	-0.868 (0.688)
Observations	607,177	607,177	565,810	565,810	986,999	986,999	185,988	185,988
R-squared	0.021		0.021		0.015		0.012	
Pseudo R2		0.028		0.033		0.040		0.032
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Table 6 reports the estimation results of Models (4) and (5). Panel A reports results based on direct evidence, and Panel B reports results based on indirect evidence. The dependent variable in columns (1), (3), (5), (7) are cumulative abnormal return (). The dependent variable in columns (2), (4), (6), (8) are price reversal (). Columns (1)-(4) divide the sample into two sub-samples of low and high analyst attention based on whether the number of analysts following is higher than the median of the same year in the same industry. Columns (5)-(8) divide the sample into two sub-samples based on whether the auditor comes from the Big Four accounting firm. All regressions include year fixed effects and industry fixed effects. The detailed definition of variables is shown in Appendix B. \*, \*\*, and \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively. Detailed definitions of variables are shown in Appendix B.

**Table 7. Internal Governance and Mispricing**

VARIABLES	State-owned		Non State-owned		Low-Independent Director		High-Independent Director	
	(1) CAR[1, 5]	(2) Reverse	(3) CAR[1, 5]	(4) Reverse	(5) CAR[1, 5]	(6) Reverse	(7) CAR[1, 5]	8 Reverse
Panel A: Direct Evidence								
Dum_manip	-0.030*** (0.006)	0.337*** (0.141)	-0.020** (0.010)	0.314 (0.268)	-0.026*** (0.008)	0.392*** (0.109)	-0.018 (0.016)	0.314 (0.238)
Price	-0.005*** (0.001)	0.269*** (0.018)	-0.007*** (0.001)	0.208*** (0.014)	-0.006*** (0.001)	0.241*** (0.015)	-0.005*** (0.001)	0.182*** (0.015)
Lagturnover	-0.168*** (0.024)	-0.366 (0.341)	-0.159*** (0.017)	0.351* (0.212)	-0.167*** (0.017)	0.020 (0.238)	-0.123*** (0.022)	-0.128 (0.268)
Intravol	0.000*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	0.002*** (0.000)
Lagvol	0.097** (0.043)	2.718*** (0.599)	0.233*** (0.046)	0.910** (0.392)	0.176*** (0.055)	2.021*** (0.494)	0.180*** (0.042)	1.022** (0.470)
Size	-0.000 (0.000)	0.047*** (0.011)	-0.002*** (0.001)	0.082*** (0.012)	-0.002*** (0.001)	0.066*** (0.011)	-0.001*** (0.000)	0.058*** (0.011)
Inst	0.000*** (0.000)	-0.005*** (0.001)	0.000*** (0.000)	-0.005*** (0.001)	0.000*** (0.000)	-0.006*** (0.001)	0.000*** (0.000)	-0.004*** (0.001)
Follow	-0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.000)	-0.000 (0.001)
Mtb	-0.013*** (0.003)	0.172** (0.074)	-0.011*** (0.003)	-0.078 (0.069)	-0.014*** (0.003)	0.089 (0.070)	-0.013*** (0.003)	0.006 (0.068)
Roa	0.014 (0.010)	-0.522*** (0.196)	0.042*** (0.008)	-0.730*** (0.161)	0.039*** (0.009)	-0.732*** (0.174)	0.032*** (0.009)	-0.486*** (0.173)
Tobinq	-0.000 (0.001)	-0.000 (0.011)	-0.001*** (0.000)	0.002 (0.007)	-0.001** (0.001)	0.012 (0.009)	-0.001** (0.000)	-0.001 (0.008)
Constant	0.030*** (0.012)	-1.823*** (0.256)	0.067*** (0.014)	-2.206*** (0.290)	0.054*** (0.013)	-2.135*** (0.275)	0.046*** (0.011)	-1.725*** (0.248)
Observations	10,220	10,220	13,110	13,110	12,272	12,272	11,058	11,058
R-squared	0.045		0.024		0.036		0.030	
Pseudo R2		0.069		0.067		0.067		0.065
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Indirect Evidence								
Dum_manip	-0.017*** (0.002)	1.998*** (0.061)	-0.008*** (0.002)	0.952*** (0.057)	-0.014*** (0.002)	1.011*** (0.225)	-0.008*** (0.003)	0.683*** (0.178)
Price	-0.006*** (0.000)	0.259*** (0.004)	-0.003*** (0.000)	0.188*** (0.004)	-0.003*** (0.000)	0.089*** (0.014)	-0.004*** (0.000)	0.067*** (0.015)
Lagturnover	-0.140*** (0.005)	0.258*** (0.085)	-0.125*** (0.004)	0.043 (0.064)	-0.127*** (0.004)	2.331*** (0.277)	-0.117*** (0.005)	2.248*** (0.250)
Intravol	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)	0.005*** (0.001)	-0.000*** (0.000)	0.002** (0.001)
Lagvol	0.052*** (0.010)	-0.805*** (0.190)	0.030*** (0.008)	-0.066 (0.055)	0.021*** (0.007)	-12.159*** (0.743)	0.076*** (0.017)	-12.662*** (0.794)
Size	0.000 (0.000)	0.013*** (0.003)	-0.000 (0.000)	0.018*** (0.003)	0.000 (0.000)	0.046*** (0.010)	-0.001*** (0.000)	0.034*** (0.011)
Inst	0.000*** (0.000)	-0.004*** (0.000)	-0.000* (0.000)	-0.003*** (0.000)	0.000 (0.000)	0.003** (0.001)	0.000** (0.000)	0.002 (0.002)
Follow	-0.000 (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.002*** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Mtb	-0.019*** (0.001)	0.352*** (0.018)	-0.018*** (0.001)	0.215*** (0.019)	-0.019*** (0.001)	0.046 (0.069)	-0.019*** (0.001)	0.090 (0.074)
Roa	0.018*** (0.002)	-0.694*** (0.037)	0.033*** (0.002)	-0.433*** (0.037)	0.022*** (0.002)	-0.587*** (0.137)	0.030*** (0.002)	-0.706*** (0.130)
Tobinq	0.000* (0.000)	0.019*** (0.003)	-0.000** (0.000)	0.018*** (0.003)	-0.000 (0.000)	-0.002 (0.013)	-0.000* (0.000)	0.024* (0.013)
Constant	0.025*** (0.003)	-1.502*** (0.062)	0.025*** (0.003)	-1.389*** (0.079)	0.021*** (0.003)	-1.669*** (0.267)	0.032*** (0.003)	-1.322*** (0.270)
Observations	571,831	571,831	601,156	601,156	655,475	655,475	517,512	517,512
R-squared	0.013		0.023		0.014		0.015	
Pseudo R2		0.039		0.044		0.040		0.041
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Table 7 reports the estimation results of Models (4) and (5). Panel A reports results based on direct evidence, and Panel B reports results based on indirect evidence. The dependent variable in columns (1), (3), (5), (7) are cumulative abnormal return ( $\Delta$ ). The dependent variable in columns (2), (4), (6), (8) are price reversal ( $\Delta$ ). In columns (1)-(4), we divide the sample into two sub-samples based on whether the company is a state-owned enterprise. In columns (5)-(8), we divide the sample into two sub-samples based on whether the proportion of independent directors on the board is higher than the industry median. All regressions include year fixed effects and industry fixed effects. \*, \*\*, and \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively. Detailed definitions of variables are shown in Appendix B.



## Online Appendices

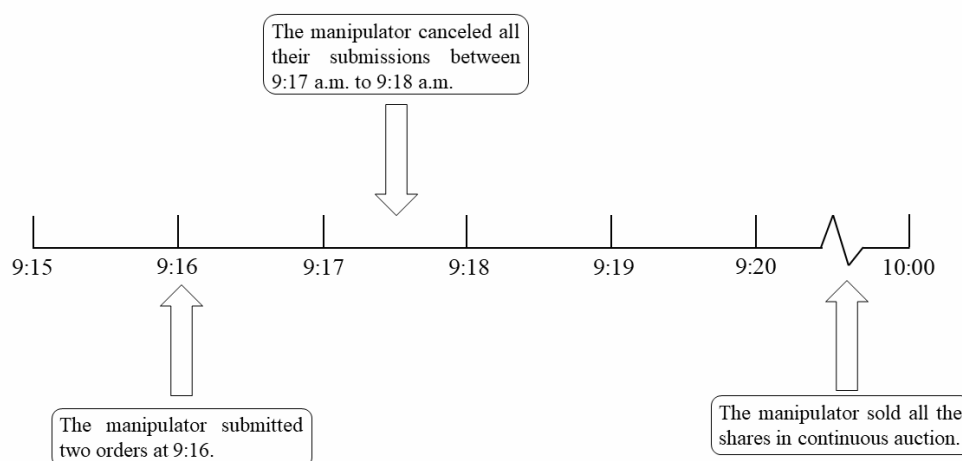
### **Appendix A. Characteristics of opening price manipulation and a typical case**

In a typical opening price manipulation case, manipulators take a trading strategy that exhibits the following characteristics:

- 1) Submitting large size orders. Manipulators often submit extremely large orders during the pre-opening call auction, taking up a significant proportion of order submissions in the market. Usually, large orders and small orders are assumed to differ greatly in terms of the market information justifying the volumes purchased. By submitting large orders, manipulators endeavor to increase the stock's price, thus misleading other investors into buying the stock by conveying false information.
- 2) Submitting buy orders at a high price. The price of the orders submitted by manipulators during pre-opening call auction are often higher than the closing price on the previous day and the average submissions price in the market during a call auction, even reaching the upper price limit. Investors are impressed by the large buy orders at a high price and manipulators are more likely to succeed in driving up the opening price.
- 3) Cancelling submissions just before the transaction is closed. By submitting large orders at a high price, manipulators mislead other investors, who will be persuaded to purchase the stock, thus helping to maintain its distorted price. Manipulators will then cancel their buy orders during the pre-opening call auction because their real intention is not to buy the stock, but to push up the stock price.
- 4) Large-scale stock selling after manipulation. After completing opening price manipulation, the manipulator will sell large quantities of the stock they hold on the manipulation day or on following trading days.

For example, as disclosed in the CSRC (2018) No.108 administrative penalty order, a manipulator account submitted two orders to buy Western Region Gold (stock code: 601069) at 9:16 a.m. on March 11<sup>th</sup>, 2016. The two orders were for 990,000 shares and 420,000 shares each, and accounted for 27% and 12% respectively of the total submissions during the pre-opening call auction. The two submissions were made at a price of 25.06 RMB per share, 10% higher than the closing price of 22.78 RMB per share on the previous day, and 3% higher than the market's average submission price during the pre-opening call auction, which was 24.33 RMB per share. After other investors followed suit and submitted buy orders, the manipulator canceled all his

orders between 9:17 a.m. and 9:18 a.m. to ensure that his submissions would not be finalized. The trading records of the manipulator are shown in Figure A. As a result of manipulation, Western Region Gold opened with a price of 23.81, 4.25% higher than the previous closing price. After that, the manipulator began to sell the stock. By 10:00 a.m., 70,300 shares had been sold by the manipulator with a profit of 76,759.43 RMB. The stock price rose to a peak of 24.17 RMB after the market opened, and closed at 23.28 RMB, which is 2.22% lower than its opening price and 3.68% lower than its highest price during the day.



**Figure A. Trading record of manipulator in Western Region Gold case**

Notes: Figure A reports the trading record of manipulator in Western Region Gold case. The trading record is disclosed in the CSRC (2018) No.108 administrative penalty order. In the case, the manipulator submitted two orders to buy Western Region Gold (stock code: 601069) at 9:16 a.m. on March 11<sup>th</sup> 2016. The two orders are of 990,000 shares and 420,000 shares each, and took up 27% and 12% respectively of the total submissions during pre-opening call auction. After other investors follow suit and submit buy orders, the manipulator canceled all of his orders between 9:17 a.m. to 9:18 a.m. to ensure that his submissions would not be finalized. Seven minutes after the market opened, the manipulator began to sell his stocks. By 10:00 a.m., 70,300 shares are sold by the manipulator with a profit of 76,759.43 RMB.

## Appendix B. Definition of Main Variables

**Table B. Definition of Main Variables**

Variable	Definition
Panel A: Main Explanatory Variables	
Dum_manip	A dummy variable indicating whether a stock is manipulated.
Panel B: Variables Measuring Mispricing	
Intra_ret[0]	The intraday abnormal return for the day of manipulation. This is specified in the following equation: $IR_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} - \frac{P_{m,t} - P_{m,t-1}}{P_{m,t-1}}$ , where $P_{i,t}$ and $P_{i,t-1}$ represent the closing price and opening price, respectively, of stock $i$ on trading day $t$ , and $P_{m,t}$ and $P_{m,t-1}$ represent the closing and opening price of the market index on trading day $t$ .
CAR[1, 5]	The cumulative abnormal return for the five trading days after the day of manipulation. This is specified in the following equation: $CAR_{i,t} = \sum_{k=1}^5 IR_{i,t-k}$ , where $IR_{i,t-k}$ is stock return on trading day $t-k$ , and $R_{m,t-k}$ is the market return.
Reverse	A dummy variable indicating whether a stock's price on the fifth day after manipulation falls below its opening price on manipulation day. This is specified in the following equation: $Reverse_{i,t} = \frac{P_{i,t+5} - P_{i,t}}{P_{i,t}}$ , where $P_{i,t+5}$ and $P_{i,t}$ represent, respectively, the closing price after five trading days and the opening price on the day of manipulation.
VWAP	$VWAP_{i,t}$ is calculated as the ratio of the trading amount to the total trading volume of the stock and is used to measure the average costs that investors pay when buying manipulated stocks on the day of manipulation (Gao et al., 2016).
Investors' loss1	For investors who buy shares of the manipulated stocks during a call auction, $loss1_{i,t}$ is computed by first calculating the return on the closing price for the three or five trading days after the day of manipulation, relative to the opening price on the day of manipulation, and then multiplying this return by the trading amount during the pre-opening call auction.
Investors' loss2	As for investors who buys the manipulated stock at $P_{i,t}$ at any time on the manipulation day, $loss2_{i,t}$ is computed by first calculating the return on the closing price for the three or five trading days after the day of manipulation, relative to the $P_{i,t}$ on the day of manipulation, and then multiplying this return by the entire day's trading amount.
Panel C: Variables Measuring Trading Activity	
AT[0]	The abnormal turnover on the manipulation day ( $AT_{i,t}$ ) is calculated by subtracting one from the ratio of the turnover on the day of manipulation to the average turnover for the 200 trading days before the day of manipulation, as the following equation: $AT_{i,t} = \frac{TO_{i,t}}{TO_{i,t-200:t-1}} - 1$ , where $TO_{i,t}$ represents the turnover of stock $i$ on trading day $t$ , and $TO_{i,t-200:t-1}$ represents the average turnover for stock $i$ for the 200 trading days before trading day $t$ .
CAT[1, 5]	The cumulative abnormal turnover for the five trading days following manipulation day.
Amihud[0]	Amihud ratio on the day of manipulation.
Amihud[1, 5]	Amihud ratio for the five trading days after manipulation.
Panel D: Variables Measuring Volatility	
Idivol[1, 5]	Idiosyncratic volatility for five trading days after manipulation. Following Che (2018), idiosyncratic volatility is calculated as the square root of the sum of squared errors from the market-model regression for five trading days after manipulation. The residual error is shown in the following equation: $Idivol_{i,t} = \sqrt{\sum_{k=1}^5 \epsilon_{i,t-k}^2}$ , where $\epsilon_{i,t-k}$ is the individual stock return for stock $i$ on trading day $t-k$ and $R_{m,t-k}$ is the market return.
CNI_retail[1, 5]	The net inflow ratio of retail trading for the five trading days after manipulation, used to determine the direction of fund flow of retail investor. We first determine the difference between the total cash inflow and the total cash outflow in transactions of less than one million RMB in value, then divide the result by the sum of the total inflow and outflow, as shown in the following equation: $CNI_{i,t} = \frac{CI_{i,t} - CO_{i,t}}{CI_{i,t} + CO_{i,t}}$ , where $CI_{i,t}$ and $CO_{i,t}$ represent the total cash inflow and outflow respectively in transactions of less than one million RMB in value for stock $i$ on trading day $t$ .
Panel E: Control Variables	
Price	The natural logarithm of the closing price on the trading day before the day of manipulation.
Lagturnover	Turnover on the trading day before the day of manipulation.
Intravol	Standard deviation of 5-minute returns on the day of manipulation.
Absret	The absolute value of return on the day of manipulation.

Lagvol	Standard deviation of daily returns for the last five trading days before manipulation.
LagAmihud5	Amihud ratio for the last five trading days before manipulation.
Size	The natural logarithm of a company's market value.
Inst	The percentage of the stock shares held by institutional investors.
Follow	The number of analysts following a listed company.
Mtb	Market-to-Book Ratio, which is the ratio of a company's book value to its market capitalization.
Roa	Return on Assets, which is the ratio of a company's net profit after tax to its total assets.
Tobinq	Tobin's Q Ratio, which is the ratio of a company's market capitalization to its total assets.

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## Appendix C. Cases of opening price manipulation

**Table C. Cases of opening price manipulation.**

Date	Listed Comapny	Stock Code	Case Document
09/03/2007	Jiangsu Zongyi Co.,Ltd	600770	CSRC Order # (2009)43
09/04/2007	Tellhow Sci-Tech Co.,Ltd	600590	CSRC Order # (2009)43
09/05/2007	Gohigh Data Networks Technology CO., Ltd	000851	CSRC Order # (2009)43
11/06/2007	Lanzhou Greatwall Electircal Co.Ltd	600192	CSRC Order # (2009)43
12/06/2007	Lanzhou Greatwall Electircal Co.Ltd	600192	CSRC Order # (2009)43
19/06/2007	Zhejiang Juhua Co.,Ltd	600160	CSRC Order # (2009)43
04/09/2007	Shenzhen Special Economic Zone Real Estate and Properties(Group) Co., Ltd	000029	CSRC Order # (2010)31
29/07/2010	Zoomlion Heavy Industry Science And Technology CO., Ltd	000157	CSRC Order # (2014)12
15/10/2010	Ningxia Orient Tantalum Industry Co., Ltd	000962	CSRC Order # (2014)12
25/10/2010	Yuannan Copper Co., Ltd	000878	CSRC Order # (2014)12
02/12/2010	Anhui Fengyuan Pharmaceutical Co., Ltd	000153	CSRC Order # (2014)12
02/12/2010	Weichai Power Co., Ltd	000338	CSRC Order # (2014)12
08/12/2010	Anhui Fengyuan Pharmaceutical Co., Ltd	000153	CSRC Order # (2014)12
06/01/2011	Yuannan Copper Co., Ltd	000878	CSRC Order # (2014)12
03/03/2011	Sichuan Shuangma Cement Co., Ltd	000935	CSRC Order # (2014)12
22/08/2011	Anhui Golden Seed Winery Co.,Ltd	600199	CSRC Order # (2014)12
28/10/2011	China South Publishing and Media Group Co.,Ltd	601098	CSRC Order # (2014)12
07/03/2012	Fujian Star-Net Communication Co., Ltd	002396	CSRC Order # (2014)12
17/12/2012	Wangneng Environment Co., Ltd	002034	CSRC Order # (2016)69
18/12/2012	Sichuan Kexin Mechanical And Electrical Equipment Co., Ltd	300092	CSRC Order # (2016)69
18/12/2012	Wangneng Environment Co., Ltd	002034	CSRC Order # (2016)69
19/12/2012	Kaiser (China) Culture Co., Ltd	002425	CSRC Order # (2016)69
19/12/2012	Sichuan Kexin Mechanical And Electrical Equipment Co., Ltd	300092	CSRC Order # (2016)69
26/12/2012	Tianjin Jingwei Huikai Optoelectronic Co., Ltd	300120	CSRC Order # (2016)69
27/12/2012	Tianjin Jingwei Huikai Optoelectronic Co., Ltd	300120	CSRC Order # (2016)69
07/01/2013	Sichuan Kexin Mechanical And Electrical Equipment Co., Ltd	300092	CSRC Order # (2016)69
09/01/2013	Guangdong Sky Dragon Printing Ink Group Co., Ltd	300063	CSRC Order # (2016)69
30/01/2013	Shanghai Morn Electric Equipment Co., Ltd	002451	CSRC Order # (2016)69

31/01/2013	Wangneng Environment Co., Ltd	002034	CSRC Order # (2016)69
04/02/2013	Jiangsu Zitian Media Technology Co., Ltd	300280	CSRC Order # (2015)58
19/02/2013	Tianjin Jingwei Huikai Optoelectronic Co., Ltd	300120	CSRC Order # (2016)69
26/02/2013	Shanghai Morn Electric Equipment Co., Ltd	002451	CSRC Order # (2016)69
20/05/2014	Gohigh Data Networks Technology Co., Ltd	000851	CSRC Order # (2018)108
21/05/2014	Zhejiang Juhua Co.,Ltd	600160	CSRC Order # (2018)108
10/06/2014	Chengdu Taide Health Tecnology Group Inc., Ltd	000790	CSRC Order # (2018)108
25/08/2014	Yingkou Port Liability Co.,Ltd	600317	CSRC Order # (2018)127
27/08/2014	Wangxiang Qianchao Co., Ltd	000559	CSRC Order # (2018)108
03/09/2014	Yingkou Port Liability Co.,Ltd	600317	CSRC Order # (2018)127
05/09/2014	Yingkou Port Liability Co.,Ltd	600317	CSRC Order # (2018)127
18/09/2014	Jiangsu Yuxing Film Technology Co., Ltd	300305	CSRC Order # (2017)30
23/09/2014	Avic Heavy Machinery Co.,Ltd	600765	CSRC Order # (2018)127
24/09/2014	Wenzhou Hongfeng Electrical Alloy Co., Ltd	300283	CSRC Order # (2017)30
29/09/2014	Hyunion Holding Co., Ltd	002537	CSRC Order # (2017)30
21/10/2014	Yingkou Port Liability Co.,Ltd	600317	CSRC Order # (2018)127
18/11/2014	Jiangsu Yuxing Film Technology Co., Ltd	300305	CSRC Order # (2017)30
27/11/2014	Ningbo Shuanglin Auto Parts Co., Ltd	300100	CSRC Order # (2017)30
28/11/2014	Yuannan Xiyi Industry Co., Ltd	002265	CSRC Order # (2017)30
05/12/2014	Gf Securities Co., Ltd	000776	CSRC Order # (2017)20
26/02/2015	Hunan Boyun New Materials Co., Ltd	002297	CSRC Order # (2017)20
23/03/2015	Hithink Royalflush Information Network Co., Ltd	300033	CSRC Order # (2017)20
25/03/2015	New Hope Liuhe Co., Ltd	000876	CSRC Order # (2017)20
13/04/2015	Western Securities Co., Ltd	002673	CSRC Order # (2015)73
22/04/2015	Jihua Group Corporation Limited	601718	CSRC Order # (2018)127
12/05/2015	Sinodata Co., Ltd	002657	CSRC Order # (2015)73
10/06/2015	Sichuan Changhong Electric Co.,Ltd	600839	CSRC Order # (2018)127
06/07/2015	Wangsu Science and Technology Co., Ltd	300017	CSRC Order # (2016)111
17/07/2015	Jiangsu Huifeng Bio Agriculture Co., Ltd	002496	CSRC Order # (2016)120
21/07/2015	Qingdao Hanhe Cable Co., Ltd	002498	CSRC Order # (2016)120
27/07/2015	Hangxiao Steel Structure Co. Ltd	600477	CSRC Order # (2018)127
27/07/2015	Cssc Science andTechnology Co.,Ltd	600072	CSRC Order # (2018)127
28/07/2015	Hongbo Co., Ltd	002229	CSRC Order # (2018)108
31/07/2015	Jiangsu Pacific Quartz Co.,Ltd	603688	CSRC Order # (2016)76
07/08/2015	Zhonghe Co., Ltd	002070	CSRC Order # (2018)13

14/08/2015	Tianguang Zhongmao Co., Ltd	002509	CSRC Order # (2016)120
26/08/2015	Jingwei Textile Machinery Co., Ltd	000666	CSRC Order # (2018)61
26/08/2015	Nanxing Machinery Co., Ltd	002757	CSRC Order # (2018)59
27/08/2015	Nanxing Machinery Co., Ltd	002757	CSRC Order # (2018)59
07/09/2015	Shandong Ruifeng Chemical Co., Ltd	300243	CSRC Order # (2018)59
07/09/2015	Jingwei Textile Machinery Co., Ltd	000666	CSRC Order # (2018)61
10/09/2015	Shanghai Shibe Hi-Tech Co.,Ltd	600604	CSRC Order # (2017)37
10/09/2015	Jingwei Textile Machinery Co., Ltd	000666	CSRC Order # (2018)61
15/09/2015	Shanghai Shibe Hi-Tech Co.,Ltd	600604	CSRC Order # (2017)37
22/09/2015	Honyu Wear - Resistant New Materials Co., Ltd	300345	CSRC Order # (2018)60
06/11/2015	Unisplendour Corporation Limited	000938	CSRC Order # (2018)13
18/01/2016	Huagong Tech Company Limited	000988	CSRC Order # (2018)108
26/02/2016	Guangdong Guan hao High-Tech Co.Ltd	600433	CSRC Order # (2018)108
07/03/2016	Yuannan Tin Co., Ltd	000960	CSRC Order # (2018)108
11/03/2016	Western Region Gold Co.,Ltd	601069	CSRC Order # (2018)108
01/04/2016	Zhejiang Asia-Pacific Mechanical and Electronic Co., Ltd	002284	CSRC Order # (2018)108
15/04/2016	Zhejiang China Commodities City Group Co.,Ltd	600415	CSRC Order # (2017)21
29/04/2016	Lomon Billions Group Co., Ltd	002601	CSRC Order # (2018)108
19/07/2016	O-Film Tech Co., Ltd	002456	CSRC Order # (2018)108
28/07/2016	Dongxu Optoelectronic Technology Co., Ltd	000413	CSRC Order # (2018)108
05/12/2016	Dalian Insulator Group Co., Ltd	002606	CSRC Order # (2018)77
26/12/2016	Newland Digital Technology Co., Ltd	000997	CSRC Order # (2018)108
26/12/2016	Shenzhen China Bicycle Company(Holding) Limited	000017	CSRC Order # (2018)108
18/01/2017	Lawton Development Co.,Ltd	600209	CSRC Order # (2018)108

Notes: Table C lists the date of manipulation, name and code of stocks involved as well as the penalty order document for all 87 cases of opening price manipulation disclosed by CSRC.



## Appendix D. Mean Difference Test

**Table D. Mean Difference Test**

Panel A: Mean Difference Test of Stock Price Performance							
Sample	Variable Name	Mean(M Group)	Mean(C Group)	Difference(M-C)	Standard Deviation	t statistic	P statistic
Direct evidence	Intra_ret[0]	-0.001	0.002	-0.002	0.003	-0.65	0.513
	CAR[1, 5]	-0.015	0.009	-0.025	0.006	-3.850	0.000***
	Reverse	0.558	0.394	0.165	0.053	3.123	0.002***
Indirect evidence	Intra_ret[0]	-0.007	0.002	-0.009	0.000	-42.773	0.000***
	CAR[1, 5]	-0.010	0.004	-0.014	0.000	-15.178	0.000***
	Reverse	0.561	0.473	0.088	0.004	24.264	0.000***
Panel B: Mean Difference Test of Trading Activity							
Direct Evidence	AT[0]	2.419	-0.032	2.451	0.089	27.365	0.000***
	CAT[1, 5]	7.345	-0.036	7.381	0.391	18.894	0.000***
	Amihud[0]	34.903	38.512	-3.609	7.768	-4.65	0.642
	Amihud[1, 5]	12.609	21.027	-8.418	4.828	-1.744	0.081*
Indirect Evidence	AT[0]	1.344	0.023	1.321	0.030	43.616	0.000***
	CAT[1, 5]	3.265	0.048	6.216	0.066	48.506	0.000***
	Amihud[0]	0.013	0.027	-0.014	0.003	-4.708	0.000***
	Amihud[1, 5]	0.003	0.004	-0.001	0.000	-1.690	0.091*
Panel C: Mean Difference Test of Volatility							
Direct Evidence	Idivol[1, 5]	0.028	0.017	0.011	0.001	9.211	0.000***
Indirect Evidence	Idivol[1, 5]	0.032	0.027	0.005	0.000	38.073	0.000***

Notes: Panel A in Table D conducts mean difference test to compare manipulated stocks against control group stocks in terms of stock price performance. Panel B in Table D conducts mean difference test to compare manipulated stocks against control group stocks in terms of trading activity. Panel C in Table D conducts mean difference test to compare manipulated stocks against control group stocks in terms of volatility. The detailed definition of variables is shown in Appendix B. \*, \*\*, \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively.

## Appendix E. Double Sort on Firm Size and State Ownership

**Table E. Double Sort on Firm Size and State Ownership**

VARIABLES		Size					
		Small		Median		Big	
		Car5	Reverse	Car5	Reverse	Car5	Reverse
Panel A: Direct Evidence							
State ownership	Low	-0.027*** (0.012)	0.610 (0.434)	-0.025 (0.023)	0.084 (0.432)	-0.003 (0.015)	0.330 (0.339)
	High	-0.046** (0.011)	1.613*** (0.493)	-0.048** (0.022)	0.810*** (0.297)	-0.028*** (0.011)	0.984*** (0.299)
Panel B: Indirect Evidence							
State ownership	Low	-0.009*** (0.003)	0.951*** (0.081)	-0.016*** (0.004)	0.926*** (0.119)	-0.002 (0.004)	0.675*** (0.132)
	High	-0.014** (0.004)	1.061*** (0.089)	-0.018** (0.004)	1.083*** (0.104)	-0.004** (0.002)	1.016*** (0.136)

Notes: We conduct an independent double sort on firm size (Small, Median and Large) and state ownership (Low and High). And we divide the sample into six sub-samples, which are 1) Small-size and Low-state-ownership, 2) Small-size and High-state- ownership, 3) Median-size and Low-state-ownership, 4) Median-size and High-state-ownership, 5) Large-size and Low-state-ownership, 6) Large-size and High-state-ownership. Baseline tests of Models (4) and (5) are repeated in six sub-samples and the regression coefficients (t-statistics) of are reported in Table E. All regressions include control variables in Table 7, year fixed effects and industry fixed effects. The detailed definition of variables is shown in Appendix B. \*, \*\*, \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively.

## Appendix F. Propensity Score Matching (PSM)

### Table F. Propensity Score Matching (PSM)

Panel A: Direct Evidence (Manipulation Probability Matched)							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CAR[1, 5]	Reverse	AT[0]	Amihud[0]	CAT[1,5]	Amihud[1,5]	Idivol[1, 5]
Dum_manip	-0.023*** (0.008)	0.354** (0.157)	0.781*** (0.740)	-0.701*** (0.048)	3.383*** (1.011)	-0.667*** (0.201)	0.043*** (0.001)
Price	-0.005*** (0.000)	0.199*** (0.010)	-0.280*** (0.052)	0.006*** (0.001)	-0.264** (0.127)	0.002*** (0.000)	0.017 (0.014)
Lagturnover	-0.145*** (0.014)	0.106 (0.174)	35.045*** (9.780)	-0.558*** (0.120)	5.450 (4.639)	-0.099*** (0.036)	0.785 (0.955)
Intravol	0.000*** (0.000)	0.002*** (0.000)	-0.000 (0.002)	-0.001*** (0.000)	-0.026*** (0.004)	-0.000* (0.000)	0.002*** (0.000)
Lagvol	0.177*** (0.036)	2.272*** (0.347)	-14.623** (6.045)	1.721*** (0.560)	30.325*** (11.163)	0.265* (0.136)	-1.645* (0.891)
Absret			3.719* (1.984)	0.877*** (0.159)	55.211*** (9.067)	0.116** (0.050)	2.197*** (0.376)
LagAmihud5							0.027 (0.025)
Size	-0.002*** (0.000)	0.068*** (0.007)	0.182*** (0.038)	-0.005*** (0.001)	0.069* (0.039)	-0.002*** (0.000)	0.026* (0.014)
Inst	0.000*** (0.000)	-0.005*** (0.001)	0.013*** (0.004)	-0.000*** (0.000)	-0.013** (0.005)	-0.000*** (0.000)	0.000 (0.001)
Follow	0.000 (0.000)	-0.000 (0.000)	0.001* (0.001)	-0.000*** (0.000)	-0.004 (0.002)	-0.000** (0.000)	-0.000* (0.000)
Mtb	-0.012*** (0.002)	0.033 (0.047)	-0.262*** (0.097)	0.012*** (0.003)	-0.725*** (0.187)	0.004*** (0.000)	0.019 (0.048)

Roa	0.033*** (0.006)	-0.615*** (0.119)	0.366 (0.517)	0.082*** (0.019)	0.679 (0.706)	0.015*** (0.005)	-0.048 (0.051)
Tobinq	-0.001*** (0.000)	0.004 (0.006)	0.019*** (0.005)	-0.001* (0.001)	-0.043 (0.026)	-0.000 (0.000)	0.015*** (0.006)
Constant	0.052*** (0.008)	-2.064*** (0.178)	-4.760*** (1.097)	0.072*** (0.019)	-0.779 (0.840)	0.030*** (0.005)	-0.172 (0.108)
Observations	174	174	174	174	174	174	174
R-squared	0.031		0.048	0.062	0.046	0.025	0.029
Pseudo R2		0.060					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

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Panel B: Indirect Evidence (Manipulation Probability Matched)

Dum_manip	-0.008** (0.004)	1.001*** (0.140)	0.757*** (0.131)	-1.302** (0.616)	3.313*** (1.008)	-1.207*** (0.242)	0.808*** (0.011)
Price	-0.002*** (0.000)	0.078*** (0.010)	-0.280*** (0.052)	5.567*** (1.082)	-0.264** (0.127)	2.113*** (0.260)	0.076*** (0.012)
Lagturnover	-0.148*** (0.005)	2.256*** (0.184)	35.045*** (9.780)	-58.396*** (19.513)	5.445 (4.640)	-98.745*** (35.654)	1.727*** (0.224)
Intravol	-0.000*** (0.000)	0.004*** (0.001)	-0.000 (0.002)	-0.615*** (0.161)	-0.026*** (0.004)	-0.062* (0.035)	-0.000 (0.000)
Lagvol	0.089*** (0.034)	-12.300*** (0.543)	-14.621** (6.044)	20.952*** (3.320)	30.315*** (11.163)	64.826* (16.105)	-1.183*** (0.402)
Absret			3.717* (1.984)	77.231*** (19.117)	55.218*** (9.068)	116.482** (50.003)	3.114*** (0.187)
LagAmihud5							0.040** (0.018)

Size	-0.002*** (0.000)	0.041*** (0.008)	0.182*** (0.038)	-5.352*** (0.848)	0.070* (0.039)	-1.720*** (0.186)	0.082*** (0.006)
Inst	-0.000*** (0.000)	0.002** (0.001)	0.013*** (0.004)	-0.436*** (0.107)	-0.013** (0.005)	-0.066*** (0.025)	0.000 (0.000)
Follow	-0.000*** (0.000)	-0.000 (0.000)	0.001* (0.001)	-0.080*** (0.029)	-0.004 (0.002)	-0.017** (0.008)	-0.000* (0.000)
Mtb	-0.019*** (0.001)	0.069 (0.050)	-0.262*** (0.097)	12.282*** (3.016)	-0.728*** (0.187)	4.160*** (0.480)	-0.030 (0.031)
Roa	0.035*** (0.003)	-0.658*** (0.093)	0.367 (0.518)	81.549*** (19.397)	0.676 (0.705)	15.262*** (5.456)	-0.245*** (0.033)
Tobinq	0.000 (0.000)	0.013 (0.009)	0.019*** (0.005)	-1.093* (0.559)	-0.043* (0.026)	-0.074 (0.131)	0.014*** (0.005)
Constant	0.057*** (0.005)	-1.506*** (0.186)	-4.760*** (1.097)	71.893*** (19.001)	-0.780 (0.840)	30.158*** (4.539)	-0.022 (0.092)
Observations	38,006	38,006	38,006	38,006	38,006	38,006	38,006
R-squared	0.013		0.112	0.047	0.107	0.046	0.053
Pseudo R2		0.007					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Notes: Table F presents our baseline results by using propensity score matching (PSM) method. In Panel A and Panel B we use the 1-to-1 matching based on the manipulation probability. Panel A reports empirical results based on direct evidence, Panel B reports empirical results based on indirect evidence. The dependent variable in column (1) is 5-day cumulative abnormal return (). The dependent variable in column (2) is price reversal (). The dependent variable in column (3) is abnormal turnover on the manipulation day (). The dependent variable in column (4) is Amihud ratio on the manipulation day (). The dependent variable in column (5) is 5-day cumulative abnormal turnover after manipulation (). The dependent variable in column (6) is Amihud ratio for 5 trading days after manipulation (). The dependent variable in column (7) is idiosyncratic volatility (). All regressions include year fixed effects and industry fixed effects. The detailed definition of variables is shown in Appendix B. \*, \*\*, \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively.

## Appendix G. Alternative Overnight Returns

**Table G Alternative Overnight Returns**

VARIABLES	(1) CAR[1, 5]	(2) Reverse	(3) AT[0]	(4) Amihud[0]	(5) CAT[1,5]	(6) Amihud[1,5]	(7) Idivol[1, 5]
Dum_manip	-0.002*** (0.001)	0.349*** (0.032)	1.308*** (0.275)	-0.064*** (0.007)	0.817*** (0.134)	-0.015*** (0.002)	0.004** (0.002)
Price	-0.005*** (0.000)	0.201*** (0.012)	-0.274*** (0.010)	0.055*** (0.003)	-0.110*** (0.034)	0.013*** (0.001)	0.026*** (0.001)
Lagturnover	-0.099*** (0.001)	-0.912*** (0.150)	34.038*** (2.219)	0.705*** (0.069)	21.111*** (0.434)	0.147*** (0.020)	0.765*** (0.010)
Intravol	-0.000*** (0.000)	0.006*** (0.000)	0.004** (0.002)	-0.001*** (0.000)	-0.010*** (0.001)	-0.000*** (0.000)	0.001*** (0.000)
Lagvol	0.046*** (0.001)	-0.361** (0.172)	-2.745*** (0.562)	1.133*** (0.209)	4.320*** (0.883)	0.281*** (0.056)	-0.519*** (0.012)
Absret			2.727*** (0.431)	2.656*** (0.106)	49.960*** (1.384)	0.500*** (0.035)	1.016*** (0.011)
LagAmihud5							0.037*** (0.000)
Size	0.001*** (0.000)	-0.091*** (0.010)	0.277*** (0.034)	0.087*** (0.005)	0.270*** (0.028)	0.019*** (0.002)	0.027*** (0.000)
Inst	0.000*** (0.000)	-0.002** (0.001)	0.013*** (0.001)	-0.001*** (0.000)	0.001 (0.001)	-0.000*** (0.000)	-0.000*** (0.000)
Follow	0.000* (0.000)	0.001*** (0.000)	0.001*** (0.000)	-0.000*** (0.000)	-0.003*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Mtb	-0.015*** (0.000)	0.214*** (0.060)	-0.390*** (0.061)	-0.200*** (0.012)	-1.274*** (0.081)	-0.047*** (0.004)	-0.020*** (0.003)
Roa	0.029*** (0.001)	-0.135 (0.126)	0.453*** (0.045)	-0.083*** (0.015)	0.564*** (0.103)	-0.016*** (0.003)	-0.054*** (0.006)
Tobinq	0.000 (0.000)	-0.003 (0.006)	0.008* (0.004)	-0.014*** (0.001)	-0.054*** (0.010)	-0.003*** (0.000)	0.004*** (0.000)
Constant	-0.005*** (0.001)	1.446*** (0.235)	-4.403*** (0.215)	0.462*** (0.024)	-3.417*** (0.266)	0.123*** (0.006)	-0.086*** (0.012)
Observations	1,002,864	1,002,864	1,002,864	1,002,864	1,002,864	1,002,864	1,002,864
R-squared	0.011		0.054	0.031	0.029	0.022	0.014

Pseudo R2		0.028						
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Table G repeats our baseline analysis by using an alternative method of calculating overnight return following Akbas et al. (2021), in which the definition of the previous overnight return is imputed from daytime return and the daily close-to-close return. The dependent variable in column (1) is 5-day cumulative abnormal return (). The dependent variable in column (2) is price reversal (). The dependent variable in column (3) is abnormal turnover on the manipulation day (). The dependent variable in column (4) is Amihud ratio on the manipulation day (). The dependent variable in column (5) is 5-day cumulative abnormal turnover after manipulation (). The dependent variable in column (6) is Amihud ratio for 5 trading days after manipulation (). The dependent variable in column (7) is idiosyncratic volatility (). All regressions include year fixed effects and industry fixed effects. The detailed definition of variables is shown in Appendix B. \*, \*\*, \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively.

## Appendix H. Bull Market and Bear Market Distribution

**Table H. Bull Market and Bear Market Distribution**

(1)	Time Period of the Sample		Direct Evidence		Indirect Evidence	
	(2)	(3)	(4)	(5)	(6)	7
Market Environment	Number of Months	Percentage of Time Period	Manipulation Cases	Percentage of All Cases	Manipulation Cases	Percentage of All Cases
Bull Market	74	56.06%	58	66.67%	10,980	57.78%
Bear Market	58	43.94%	29	33.33%	8,023	42.22%
Total	132	100%	87%	100%	19,003	100%

Notes: Table H lists the distributions for the bull as well as bear market in the sampling interval. Following Chen (2009), we divide the market environment for the samples into bear market and bull market based on the moving average of the market returns. When the average rate of return in recent 5 months is greater than 0, the market is in a bull market, otherwise it is a bear market. Columns (4) - (5) report empirical results based on direct evidence, and columns (6) - (7) report empirical results based on indirect evidence.



## Appendix I. Impact of Manipulation in the Bull Market and the Bear Market

### Table I. Impact of Manipulation in the Bull Market and the Bear Market

Panel A: Direct Evidence (Bull Market)							
VARIABLES	(1) CAR[1, 5]	(2) Reverse	(3) AT[0]	(4) Amihud[0]	(5) CAT[1,5]	(6) Amihud[1,5]	(7) Idivol[1, 5]
Dum_manip	-0.035*** (0.08)	0.457** (0.196)	1.477*** (0.077)	-2.029*** (0.066)	4.337*** (1.359)	-0.772*** (0.284)	2.099*** (0.255)
Price	-0.009*** (0.001)	0.221*** (0.014)	-0.297*** (0.043)	1.460 (2.324)	-0.631*** (0.218)	1.140* (0.631)	0.029 (0.024)
Lagturnover	-0.185*** (0.018)	0.261 (0.215)	36.210*** (12.593)	-764.193*** (167.929)	-11.467* (6.938)	-128.147** (50.847)	1.097 (1.401)
Intravol	0.000*** (0.000)	0.004*** (0.000)	-0.002 (0.003)	-0.823*** (0.235)	-0.033*** (0.005)	-0.092* (0.050)	0.002*** (0.001)
Lagvol	0.216*** (0.059)	2.189*** (0.476)	-12.874* (6.835)	2,669.074*** (953.440)	48.129*** (18.467)	412.082* (219.598)	-2.090 (1.617)
Absret			3.494* (2.083)	1,084.123*** (203.167)	61.447*** (11.980)	156.159** (65.785)	2.972*** (0.523)
LagAmihud5							0.024 (0.024)
Size	-0.001*** (0.000)	0.063*** (0.010)	0.201*** (0.052)	-7.461*** (1.545)	-0.024 (0.069)	-1.876*** (0.345)	0.038* (0.022)
Inst	0.000*** (0.000)	-0.007*** (0.001)	0.014*** (0.005)	-0.598*** (0.147)	-0.024*** (0.008)	-0.085** (0.033)	0.000 (0.001)
Follow	-0.000 (0.000)	-0.000 (0.000)	0.001** (0.001)	-0.058 (0.043)	-0.005 (0.003)	-0.015 (0.009)	-0.000 (0.000)
Mtb	-0.020*** (0.003)	0.204*** (0.062)	-0.223* (0.118)	9.809** (4.789)	-0.748** (0.298)	3.170*** (0.772)	0.043 (0.075)
Roa	0.032*** (0.009)	-0.286* (0.155)	0.105 (0.605)	143.318*** (35.449)	3.151*** (1.182)	24.141** (9.761)	-0.076 (0.085)
Tobinq	-0.001*** (0.000)	0.014* (0.008)	0.029*** (0.009)	-2.319** (0.980)	-0.096** (0.040)	-0.270 (0.218)	0.026*** (0.009)
Constant	0.060*** (0.012)	-2.118*** (0.233)	-5.347*** (1.613)	114.954*** (35.223)	2.709* (1.502)	33.522*** (7.990)	-0.258 (0.183)
Observations	14,882	14,882	14,882	14,882	14,882	14,882	14,882

R-squared	0.043		0.046	0.093	0.055	0.034	0.033
Pseudo R2		0.097					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Panel B: Direct Evidence (Bear Market)							
Dum_manip	-0.030** (0.014)	0.268** (0.129)	1.233*** (0.348)	-1.317 (1.078)	1.837 (1.266)	-0.332 (0.366)	0.214 (0.234)
Price	0.001 (0.001)	0.159*** (0.019)	-0.111*** (0.007)	5.046*** (0.230)	-0.247*** (0.035)	2.906*** (0.135)	0.001*** (0.000)
Lagturnover	-0.030 (0.019)	3.561*** (0.423)	9.504*** (0.364)	-81.046*** (3.551)	27.799*** (1.269)	-29.077*** (1.710)	0.028 (0.025)
Intravol	-0.000*** (0.000)	-0.020*** (0.002)	0.010*** (0.001)	-0.016 (0.010)	0.009*** (0.003)	0.044*** (0.009)	0.000** (0.000)
Lagvol	0.191*** (0.030)	-12.088*** (0.844)	0.844* (0.507)	-29.560*** (5.156)	13.047*** (2.363)	-26.166*** (3.521)	-0.245 (0.157)
Absret			7.911*** (0.431)	184.255*** (6.993)	24.625*** (1.797)	-5.238** (2.451)	0.091*** (0.031)
LagAmihud5							0.006 (0.004)
Size	-0.001*** (0.000)	0.066*** (0.013)	0.068*** (0.005)	-3.439*** (0.133)	0.123*** (0.025)	-1.729*** (0.105)	0.001** (0.001)
Inst	0.000*** (0.000)	-0.001 (0.001)	0.003*** (0.000)	-0.018** (0.008)	0.008*** (0.002)	-0.014*** (0.004)	0.000 (0.000)
Follow	-0.000 (0.000)	0.001 (0.001)	0.001*** (0.000)	-0.006 (0.004)	0.003** (0.001)	-0.002 (0.003)	-0.000 (0.000)
Mtb	-0.004 (0.003)	-0.392*** (0.085)	-0.072** (0.032)	11.572*** (0.677)	-0.551*** (0.159)	5.484*** (0.515)	-0.003 (0.005)
Roa	0.035*** (0.008)	-1.487*** (0.218)	-0.062 (0.075)	8.062*** (1.341)	-0.643* (0.391)	3.400*** (0.792)	-0.005 (0.004)
Tobinq	-0.001 (0.000)	0.002 (0.011)	0.015*** (0.004)	0.504*** (0.059)	0.025 (0.019)	0.224*** (0.038)	-0.000 (0.000)
Constant	0.036*** (0.011)	-2.295*** (0.319)	-1.710*** (0.119)	61.792*** (2.949)	-3.024*** (0.585)	32.030*** (2.222)	-0.002 (0.003)
Observations	8,448	8,448	8,448	8,448	8,448	8,448	8,448
R-squared	0.029		0.548	0.449	0.300	0.215	0.079
Pseudo R2		0.204					

Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Panel C: Indirect Evidence (Bull Market)							
Dum_manip	-0.069*** (0.008)	0.809*** (0.026)	0.513*** (0.112)	-0.071*** (0.009)	1.330*** (0.206)	-0.016*** (0.002)	0.041*** (0.006)
Price	0.000 (0.001)	0.128*** (0.003)	-0.461*** (0.031)	0.014*** (0.005)	-0.261*** (0.049)	0.002*** (0.001)	0.032*** (0.002)
Lagturnover	0.208*** (0.013)	0.746*** (0.058)	45.315*** (3.213)	-2.027*** (0.102)	0.263 (1.570)	-0.469*** (0.036)	0.863*** (0.071)
Intravol	0.000 (0.000)	-0.004*** (0.000)	-0.000 (0.003)	-0.001*** (0.000)	-0.016*** (0.001)	-0.000*** (0.000)	0.001 (0.000)
Lagvol	0.045 (0.028)	-0.693*** (0.124)	-3.097*** (0.726)	0.868*** (0.201)	3.142*** (1.045)	0.248*** (0.062)	-0.393*** (0.058)
Absret			0.716 (0.923)	3.500*** (0.168)	72.142*** (2.526)	0.759*** (0.059)	1.051*** (0.278)
LagAmihud5							0.026*** (0.007)
Size	-0.001** (0.000)	0.011*** (0.002)	0.250*** (0.020)	-0.024*** (0.001)	-0.095*** (0.026)	-0.006*** (0.000)	0.032*** (0.001)
Inst	0.000*** (0.000)	-0.004*** (0.000)	0.021*** (0.002)	-0.001*** (0.000)	-0.006*** (0.002)	-0.000*** (0.000)	-0.000*** (0.000)
Follow	0.000*** (0.000)	-0.000 (0.000)	0.001* (0.000)	-0.000*** (0.000)	-0.005*** (0.001)	-0.000*** (0.000)	-0.000*** (0.000)
Mtb	-0.003 (0.002)	0.420*** (0.013)	-0.363*** (0.066)	-0.048*** (0.010)	-1.109*** (0.123)	-0.020*** (0.003)	-0.027*** (0.005)
Roa	0.019*** (0.006)	-0.823*** (0.029)	1.056*** (0.136)	0.204*** (0.040)	1.954*** (0.241)	0.048*** (0.007)	-0.080*** (0.006)
Tobinq	-0.001 (0.000)	0.032*** (0.002)	0.025*** (0.005)	-0.004* (0.002)	-0.111*** (0.014)	-0.002*** (0.000)	0.006*** (0.001)
Constant	0.026*** (0.009)	-0.781*** (0.035)	-6.614*** (0.504)	0.508*** (0.036)	0.284 (0.551)	0.129*** (0.010)	-0.197*** (0.014)
Observations	2,032,023	2,032,023	2,032,023	2,032,023	2,032,023	2,032,023	2,032,023
R-squared	0.009		0.054	0.035	0.021	0.025	0.011
Pseudo R2		0.006					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Panel D: Indirect Evidence (Bear Market)							
Dum_manip	-0.004*** (0.000)	0.650*** (0.024)	0.363*** (0.104)	-0.008** (0.004)	0.539** (0.268)	-0.005* (0.003)	0.007 (0.010)
Price	-0.003*** (0.000)	0.075*** (0.003)	-0.189*** (0.009)	0.016*** (0.001)	-0.405*** (0.017)	0.005*** (0.000)	0.009*** (0.001)
Lagturnover	-0.072*** (0.002)	-1.167*** (0.057)	17.959*** (0.998)	-0.864*** (0.079)	34.046*** (0.524)	-0.198*** (0.018)	0.468*** (0.043)
Intravol	-0.000*** (0.000)	0.004*** (0.000)	0.006*** (0.001)	-0.001*** (0.000)	-0.000 (0.001)	-0.000*** (0.000)	-0.000 (0.000)
Lagvol	0.058*** (0.009)	-0.352** (0.142)	-1.885*** (0.595)	1.701*** (0.480)	3.215*** (0.922)	0.332*** (0.102)	-0.305*** (0.059)
Absret			3.244*** (0.258)	1.120*** (0.076)	23.837*** (0.679)	0.112*** (0.016)	1.109 (0.724)
LagAmihud5							0.046*** (0.013)
Size	0.000*** (0.000)	-0.070*** (0.002)	0.079*** (0.004)	-0.011*** (0.001)	0.159*** (0.008)	-0.004*** (0.000)	0.013*** (0.002)
Inst	0.000*** (0.000)	-0.001*** (0.000)	0.008*** (0.000)	-0.001*** (0.000)	0.013*** (0.001)	-0.000*** (0.000)	-0.000*** (0.000)
Follow	-0.000*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	-0.000*** (0.000)	0.001*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Mtb	-0.012*** (0.000)	0.347*** (0.015)	-0.061*** (0.012)	0.004 (0.004)	-0.629*** (0.043)	0.003*** (0.001)	-0.006 (0.004)
Roa	0.029*** (0.001)	-0.514*** (0.033)	0.294*** (0.035)	0.049*** (0.009)	0.675*** (0.091)	0.015*** (0.002)	-0.037*** (0.005)
Tobinq	0.000* (0.000)	-0.018*** (0.002)	0.027*** (0.002)	0.001 (0.001)	0.073*** (0.007)	0.000 (0.000)	0.004*** (0.001)
Constant	0.010*** (0.001)	1.206*** (0.040)	-2.325*** (0.090)	0.166*** (0.025)	-4.788*** (0.184)	0.064*** (0.005)	-0.076*** (0.011)
Observations	2,902,604	2,902,604	2,902,604	2,902,604	2,902,604	2,902,604	2,902,604
R-squared	0.007		0.093	0.013	0.066	0.024	0.019
Pseudo R2		0.007					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Notes: Table I reports the regression result of opening price manipulation under the heterogeneity of market environment. Panel A and Panel B report empirical results based

on direct evidence, Panel C and Panel D report empirical results based on indirect evidence. The distribution of bull market and bear market is shown in table H. The dependent variable in column (1) is 5-day cumulative abnormal return (). The dependent variable in column (2) is price reversal (). The dependent variable in column (3) is abnormal turnover on the manipulation day (). The dependent variable in column (4) is Amihud ratio on the manipulation day (). The dependent variable in column (5) is 5-day cumulative abnormal turnover after manipulation (). The dependent variable in column (6) is Amihud ratio for 5 trading days after manipulation (). The dependent variable in column (7) is idiosyncratic volatility (). All regressions include year fixed effects and industry fixed effects. The detailed definition of variables is shown in Appendix B. \*, \*\*, \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively.

## Appendix J. Impact of Manipulation in the Crash Period and the Bubble Period

**Table J. Impact of Manipulation in the Crash Period and the Bubble Period**

Panel A: Direct Evidence (Crash)							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CAR[1, 5]	Reverse	AT[0]	Amihud[0]	CAT[1,5]	Amihud[1,5]	Idivol[1, 5]
Dum_manip	-0.018*** (0.004)	0.179*** (0.065)	1.357** (0.615)	-2.801*** (0.765)	6.604*** (1.941)	-1.421** (0.605)	0.407*** (0.021)
Price	-0.017*** (0.002)	0.055* (0.031)	-0.178*** (0.017)	6.417*** (1.674)	-0.246 (0.182)	3.682*** (0.256)	-0.065 (0.050)
Lagturnover	-0.207*** (0.034)	0.538 (0.385)	7.278*** (0.864)	-409.919*** (95.155)	-29.643*** (10.778)	-22.937*** (3.256)	3.670 (2.929)
Intravol	0.000*** (0.000)	-0.003*** (0.000)	0.004*** (0.000)	-0.113*** (0.031)	-0.002 (0.003)	0.001 (0.002)	0.002*** (0.000)
Lagvol	0.578*** (0.063)	-10.424*** (0.796)	3.119*** (1.114)	1,319.975*** (388.397)	154.732*** (37.243)	13.817 (13.234)	-0.874 (2.780)
Absret			5.534*** (0.428)	463.549*** (105.251)	60.455*** (11.225)	4.561 (3.830)	5.194*** (1.039)
LagAmihud5							1.540 (1.239)
Size	0.007*** (0.002)	-0.096*** (0.023)	0.077*** (0.017)	-7.003*** (1.135)	-0.225 (0.144)	-1.873*** (0.090)	0.155* (0.084)
Inst	0.000 (0.000)	-0.003 (0.002)	0.006*** (0.001)	-0.449*** (0.124)	-0.021** (0.011)	-0.043*** (0.009)	0.003 (0.002)
Follow	0.000*** (0.000)	-0.002* (0.001)	0.004*** (0.001)	-0.020 (0.034)	0.012*** (0.005)	-0.014*** (0.004)	-0.001 (0.001)
Mtb	-0.003 (0.010)	-0.054 (0.146)	-0.403*** (0.093)	12.992*** (4.618)	-0.342 (0.807)	3.884*** (0.632)	-0.068 (0.258)
Roa	0.088*** (0.025)	-0.709** (0.346)	-0.549*** (0.164)	60.595*** (23.167)	0.005 (2.115)	1.421 (1.705)	0.020 (0.281)
Tobinq	-0.001 (0.001)	0.006 (0.015)	0.008 (0.009)	-0.097 (0.451)	-0.002 (0.072)	0.116 (0.090)	0.065** (0.025)
Constant	-0.130*** (0.034)	3.063*** (0.538)	-1.868*** (0.345)	100.224*** (19.986)	0.002 (2.636)	33.945*** (1.997)	-1.240 (0.810)
Observations	7,809	7,799	7,809	7,809	7,809	7,809	7,789

R-squared	0.080		0.410	0.206	0.141	0.196	0.080
Pseudo R2		0.064					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Panel B: Direct Evidence (Bubble)							
Dum_manip	-0.007 (0.011)	0.209 (0.273)	0.929*** (0.327)	-4.426 (3.444)	1.655 (1.135)	-0.622 (0.569)	4.884 (4.748)
Price	-0.008*** (0.001)	0.410*** (0.024)	-0.372*** (0.013)	-4.542 (5.061)	-2.081*** (0.110)	1.795*** (0.150)	0.046 (0.034)
Lagturnover	-0.017 (0.029)	-1.537*** (0.417)	12.863*** (0.626)	-853.606*** (297.594)	11.835** (5.391)	-34.857*** (7.801)	-1.242 (1.342)
Intravol	-0.000*** (0.000)	-0.002 (0.001)	0.015*** (0.001)	-2.849*** (1.058)	-0.029 (0.019)	-0.025 (0.027)	0.010 (0.010)
Lagvol	0.019 (0.038)	6.657*** (1.173)	-0.839** (0.398)	41.498* (13.888)	40.400* (23.473)	41.189 (29.265)	-2.994 (2.961)
Absret			7.022*** (0.551)	86.718*** (15.208)	43.290*** (12.716)	33.024* (17.927)	-0.134 (0.673)
LagAmihud5							0.065 (0.047)
Size	-0.002** (0.001)	0.068*** (0.015)	0.113*** (0.009)	-10.971*** (4.032)	0.122 (0.091)	-1.274*** (0.092)	-0.002 (0.011)
Inst	0.000*** (0.000)	-0.008*** (0.002)	0.004*** (0.001)	-0.687** (0.282)	-0.010 (0.006)	-0.025*** (0.009)	-0.002 (0.001)
Follow	-0.000*** (0.000)	0.002*** (0.001)	0.001*** (0.000)	-0.026 (0.069)	-0.001 (0.002)	-0.009*** (0.003)	0.001 (0.001)
Mtb	-0.038*** (0.005)	0.633*** (0.100)	-0.087 (0.055)	7.665 (9.681)	-0.921*** (0.317)	3.696*** (0.625)	0.089 (0.082)
Roa	0.003 (0.014)	-0.239 (0.248)	0.124 (0.130)	157.373** (66.986)	2.373* (1.410)	4.946*** (1.532)	-0.063 (0.053)
Tobinq	-0.001 (0.001)	0.034*** (0.012)	0.009 (0.006)	-2.761 (2.100)	-0.035 (0.044)	0.177*** (0.064)	0.011 (0.008)
Constant	0.078*** (0.018)	-2.935*** (0.361)	-2.456*** (0.221)	234.867** (93.974)	2.398 (2.060)	25.908*** (2.311)	0.111 (0.148)
Observations	15,329	15,329	15,329	15,329	15,329	15,329	15,313
R-squared	0.040		0.466	0.102	0.088	0.129	0.051
Pseudo R2		0.075					

Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Panel C: Indirect Evidence (Crash)							
Dum_manip	-0.020*** (0.001)	0.066*** (0.018)	1.578*** (0.394)	-0.087*** (0.024)	1.750*** (0.516)	-0.017*** (0.006)	0.206*** (0.023)
Price	-0.008*** (0.000)	0.237*** (0.003)	-0.297*** (0.032)	-0.011 (0.027)	-0.652*** (0.098)	0.001 (0.004)	0.077*** (0.008)
Lagturnover	-0.165*** (0.005)	-0.544*** (0.051)	39.563*** (5.229)	-1.705*** (0.252)	25.714*** (2.287)	-0.323*** (0.093)	1.909*** (0.306)
Intravol	-0.000 (0.000)	0.001*** (0.000)	0.002 (0.004)	-0.001*** (0.000)	-0.021*** (0.001)	-0.000** (0.000)	-0.001* (0.000)
Lagvol	-0.006* (0.003)	-0.381*** (0.069)	-2.909*** (1.059)	0.999** (0.459)	4.770** (2.399)	0.273 (0.213)	-0.813*** (0.169)
Absret			-1.555 (1.768)	2.736*** (0.397)	36.971*** (3.536)	0.530*** (0.178)	2.302* (1.247)
LagAmihud5							0.116** (0.046)
Size	0.001*** (0.000)	-0.021*** (0.002)	0.140*** (0.025)	-0.026*** (0.006)	0.007 (0.049)	-0.005*** (0.001)	0.062*** (0.006)
Inst	0.000*** (0.000)	-0.003*** (0.000)	0.017*** (0.003)	-0.001*** (0.000)	-0.014*** (0.004)	-0.000*** (0.000)	-0.000 (0.000)
Follow	0.000*** (0.000)	-0.001*** (0.000)	0.008*** (0.002)	-0.000 (0.000)	0.004 (0.004)	0.000 (0.000)	-0.001*** (0.000)
Mtb	-0.022*** (0.001)	0.295*** (0.014)	0.037 (0.121)	0.001 (0.065)	-0.769*** (0.298)	-0.017 (0.016)	0.025 (0.023)
Roa	0.041*** (0.002)	-0.623*** (0.026)	1.711*** (0.367)	0.374 (0.237)	2.376*** (0.561)	0.069** (0.029)	-0.197*** (0.020)
Tobinq	-0.001*** (0.000)	0.012*** (0.002)	0.002 (0.011)	0.008 (0.016)	-0.155*** (0.045)	-0.001 (0.002)	0.028*** (0.006)
Constant	0.010*** (0.003)	-0.511*** (0.051)	-4.547*** (0.759)	0.592*** (0.134)	0.319 (1.122)	0.121*** (0.026)	-0.298*** (0.078)
Observations	637,860	637,860	637,860	637,860	637,860	637,860	637,089
R-squared	0.015		0.055	0.018	0.043	0.027	0.037
Pseudo R2		0.022					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES



Panel D: Indirect Evidence (Bubble)							
Dum_manip	-0.003** (0.001)	0.832*** (0.071)	1.331*** (0.188)	-0.213*** (0.012)	1.118*** (0.292)	-0.302*** (0.003)	0.023** (0.010)
Price	-0.009*** (0.000)	0.231*** (0.014)	-0.281*** (0.025)	0.019*** (0.002)	-0.547*** (0.037)	0.004*** (0.000)	0.092*** (0.007)
Lagturnover	-0.127*** (0.008)	0.926*** (0.162)	29.094*** (3.013)	-0.876*** (0.062)	23.168*** (1.435)	-0.154*** (0.016)	2.022*** (0.255)
Intravol	-0.000*** (0.000)	0.002*** (0.000)	0.005** (0.002)	-0.000*** (0.000)	-0.008*** (0.001)	0.000 (0.000)	-0.000 (0.000)
Lagvol	0.026*** (0.010)	0.110 (0.420)	-1.909*** (0.686)	0.276 (0.175)	-1.438** (0.576)	0.063 (0.041)	-0.972*** (0.178)
Absret			1.339*** (0.469)	0.804*** (0.036)	21.992*** (0.977)	0.017** (0.008)	1.228*** (0.319)
LagAmihud5							0.018** (0.009)
Size	0.003*** (0.000)	0.157*** (0.011)	0.089*** (0.013)	-0.018*** (0.001)	0.020 (0.023)	-0.005*** (0.000)	0.064*** (0.005)
Inst	-0.000 (0.000)	-0.005*** (0.001)	0.013*** (0.001)	-0.000*** (0.000)	0.018*** (0.001)	-0.000** (0.000)	-0.002*** (0.000)
Follow	-0.000*** (0.000)	0.002*** (0.001)	0.004*** (0.000)	-0.000** (0.000)	0.005*** (0.001)	-0.000 (0.000)	-0.000*** (0.000)
Mtb	-0.026*** (0.001)	0.451*** (0.067)	0.135*** (0.039)	-0.013* (0.007)	-0.454*** (0.075)	-0.001 (0.001)	-0.028** (0.012)
Roa	0.025*** (0.003)	-0.540*** (0.139)	0.691*** (0.099)	-0.006 (0.017)	1.102*** (0.133)	-0.001 (0.003)	-0.125*** (0.021)
Tobinq	0.001*** (0.000)	0.019*** (0.007)	0.028*** (0.004)	0.001 (0.002)	0.056*** (0.016)	0.000 (0.000)	-0.002 (0.002)
Constant	-0.041*** (0.004)	-5.462*** (0.261)	-3.335*** (0.353)	0.370*** (0.031)	-2.435*** (0.520)	0.098*** (0.006)	-0.260*** (0.041)
Observations	659,673	659,673	659,673	659,673	659,673	659,673	658,621
R-squared	0.019		0.102	0.050	0.036	0.029	0.012
Pseudo R2		0.056					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Notes: Table J reports the regression result of opening price manipulation under the heterogeneity of market environment. Panel A and Panel B report empirical results based

on direct evidence, Panel C and Panel D report empirical results based on indirect evidence. Following Cumming et al.(2020) and Han and Liang(2017), we define the period from August 2007 to December 2008 and from June 2015 to September 2015 as the Chinese stock market crash sample. Meanwhile, the period from January 2007 to July 2007 and July 2014 to June 2015 are regarded as the Chinese stock market bubble sample. The dependent variable in column (1) is 5-day cumulative abnormal return (). The dependent variable in column (2) is price reversal (). The dependent variable in column (3) is abnormal turnover on the manipulation day (). The dependent variable in column (4) is Amihud ratio on the manipulation day (). The dependent variable in column (5) is 5-day cumulative abnormal turnover after manipulation (). The dependent variable in column (6) is Amihud ratio for 5 trading days after manipulation (). The dependent variable in column (7) is idiosyncratic volatility (). All regressions include year fixed effects and industry fixed effects. The detailed definition of variables is shown in Appendix B. \*, \*\*, \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively.

## Appendix K. Different Risk Factor Adjustment

**Table K. Different Risk Factor Adjustment**

VARIABLES	Direct Evidence			Indirect Evidence		
	(1) FF3F	(2) Carhart	(3) FF5F	(4) FF3F	(5) Carhart	(6) FF5F
Dum_manip	-0.050*** (0.009)	-0.069*** (0.015)	-0.044*** (0.014)	-0.015*** (0.001)	-0.014*** (0.001)	-0.014*** (0.001)
Price	0.012*** (0.002)	0.008*** (0.002)	-0.002* (0.001)	-0.004*** (0.000)	-0.002*** (0.000)	-0.006*** (0.000)
Lagturnover	-0.076* (0.042)	-0.112* (0.063)	-0.091*** (0.029)	-0.054*** (0.003)	-0.095*** (0.004)	-0.056*** (0.005)
Intravol	-0.001*** (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Lagvol	-0.068 (0.134)	0.089 (0.152)	0.045 (0.048)	-0.001 (0.005)	-0.000 (0.004)	0.253*** (0.015)
Size	-0.000 (0.001)	-0.002 (0.001)	-0.004*** (0.001)	-0.000*** (0.000)	-0.000*** (0.000)	0.002*** (0.000)
Inst	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Follow	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)
Mtb	-0.036*** (0.010)	-0.047*** (0.011)	-0.021*** (0.004)	-0.011*** (0.001)	-0.020*** (0.001)	-0.010*** (0.001)
Roa	0.028 (0.025)	-0.025 (0.031)	-0.013 (0.009)	0.027*** (0.002)	0.024*** (0.004)	0.009*** (0.002)
Tobinq	-0.005** (0.002)	-0.005** (0.002)	-0.002*** (0.001)	-0.000** (0.000)	-0.000 (0.000)	0.000** (0.000)
Constant	0.006 (0.035)	0.048 (0.034)	0.104*** (0.013)	0.022*** (0.002)	0.025*** (0.003)	-0.025*** (0.003)
Observations	23,330	23,330	23,330	1,172,987	1,172,987	1,172,987
R-squared	0.152	0.193	0.068	0.010	0.016	0.014
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Notes: Table K reports the regression result of opening price manipulation on stock price performance after risk adjustments. Columns (1) - (3) report empirical results based on direct evidence, and columns (4) - (6) report empirical results based on indirect evidence. Columns (1) and (4) reports the regression result after risk factor adjustments by Fama-French three factor model (FF3F), columns (2) and (5) reports the regression result after risk factor adjustments by Carhart four factor model (Carhart), and columns (3) and (6) reports the regression result after risk factor adjustments by Fama-French five factor model (FF5F). Of these three combinations, Fama-French three factor model includes the size factor (SMB), the book-to-market ration factor (HML) and the market factor (MKT). Carhart four factor model includes the size factor (SMB), the book to market ratio factor (HML), the market factor (MKT) and the momentum factor (UMD). And Fama-French five factor model includes the size factor (SMB), the book to market ratio factor (HML), the market factor (MKT), the profitability factor (RMW) and the investment factor (CMA). All regressions include year fixed effects and industry fixed effects. The detailed definition of variables is shown in Appendix B. \*, \*\*, \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively.

## Appendix L. Different Time Windows

**Table L. Different Time Windows**

VARIABLES	Direct Evidence				Indirect Evidence			
	(1) CAR[1, 10]	(2) Reverese10	(3) CAR[1, 20]	(4) Reverese20	(5) CAR[1, 10]	(6) Reverese10	(7) CAR[1, 20]	(8) Reverese20
Dum_manip	-0.024** (0.009)	0.338* (0.174)	-0.023*** (0.008)	0.327** (0.159)	-0.04*** (0.000)	0.812*** (0.029)	-0.003*** (0.000)	0.394*** (0.024)
Price	-0.005*** (0.001)	0.209*** (0.012)	-0.005*** (0.001)	0.206*** (0.011)	-0.005*** (0.000)	0.134*** (0.004)	-0.004*** (0.000)	0.189*** (0.004)
Lagturnover	-0.150*** (0.015)	-0.696*** (0.206)	-0.149*** (0.014)	-0.043 (0.179)	-0.093*** (0.002)	0.284*** (0.068)	-0.100*** (0.002)	-0.747*** (0.085)
Intravol	0.000*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	0.002*** (0.000)	-0.000*** (0.000)	0.003*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)
Lagvol	0.192*** (0.045)	5.066*** (0.510)	0.175*** (0.037)	1.483*** (0.337)	0.008*** (0.002)	0.524*** (0.098)	0.021*** (0.003)	-0.539*** (0.133)
Size	-0.002*** (0.000)	0.059*** (0.009)	-0.002*** (0.000)	0.062*** (0.008)	0.001*** (0.000)	0.035*** (0.003)	0.000*** (0.000)	-0.007** (0.003)
Inst	0.000*** (0.000)	-0.006*** (0.001)	0.000*** (0.000)	-0.005*** (0.001)	0.000*** (0.000)	-0.004*** (0.000)	0.000*** (0.000)	-0.003*** (0.000)
Follow	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)
Mtb	-0.022*** (0.003)	0.189*** (0.056)	-0.014*** (0.002)	0.070 (0.049)	-0.017*** (0.000)	0.249*** (0.018)	-0.017*** (0.000)	0.309*** (0.020)
Roa	0.031*** (0.008)	-0.556*** (0.142)	0.035*** (0.006)	-0.599*** (0.124)	0.025*** (0.001)	-0.505*** (0.042)	0.026*** (0.001)	-0.518*** (0.033)
Tobinq	-0.002*** (0.000)	0.019*** (0.007)	-0.001*** (0.000)	0.006 (0.006)	0.000 (0.000)	0.012*** (0.002)	-0.000 (0.000)	0.025*** (0.004)
Constant	0.063*** (0.010)	-1.950*** (0.209)	0.051*** (0.009)	-1.908*** (0.184)	0.006*** (0.001)	-1.426*** (0.067)	0.009*** (0.001)	-1.426*** (0.067)
Observations	23,330	23,330	23,330	1,172,987	1,172,987	1,172,987	1,172,987	1,172,987
R-squared	0.040		0.032	0.010	0.010		0.011	
Pseudo R2		0.074		0.063		0.007		0.009
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
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Notes: Table L reports the regression result of opening price manipulation on stock price performance under different time windows. Columns (1) - (4) report empirical results based on direct evidence, and columns (5) - (8) report empirical results based on indirect evidence. The dependent variable in columns (1) and (5) are 10-day cumulative abnormal return ( $\Delta R_{i,t}$ ). The dependent variable in columns (2) and (6) are the probability of price reversal with the time window of 10 trading days ( $P_{i,t}$ ). The dependent variable in columns (3) and (7) are 20-day cumulative abnormal return ( $\Delta R_{i,t}$ ). The dependent variable in columns (4) and (8) are the probability of price reversal with the time window of 20 trading days ( $P_{i,t}$ ). All regressions include year fixed effects and industry fixed effects. The detailed definition of control variables is shown in Appendix B. \*, \*\*, \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively.

## Appendix M. Different Control Group Selection

**Table M. Different Control Group Selection**

Panel A: Direct Evidence (Size Matched)							
VARIABLES	(1) CAR[1, 5]	(2) Reverse	(3) AT[0]	(4) Amihud[0]	(5) CAT[1,5]	(6) Amihud[1,5]	(7) Idivol[1, 5]
Dum_manip	-0.023*** (0.008)	0.665*** (0.157)	1.337** (0.640)	-2.231*** (0.739)	3.398*** (1.024)	-1.330** (0.557)	1.485*** (0.535)
Price	-0.005*** (0.001)	0.204*** (0.011)	-0.232*** (0.018)	49.314*** (4.465)	-0.242 (0.154)	5.235*** (0.390)	0.019 (0.016)
Lagturnover	-0.147*** (0.015)	0.007 (0.187)	25.916** (10.917)	508.691*** (187.178)	5.611** (2.299)	9.602 (10.831)	0.906 (1.099)
Intravol	0.000*** (0.000)	0.002*** (0.000)	-0.001 (0.002)	0.063 (0.044)	-0.025*** (0.004)	0.042*** (0.003)	0.002*** (0.000)
Lagvol	0.179*** (0.039)	1.265*** (0.342)	-9.578** (4.843)	1,294.049* (766.095)	31.412** (12.518)	99.683 (90.833)	-1.761* (1.007)
Absret			5.736*** (1.208)	961.687*** (71.894)	56.340*** (10.402)	11.649*** (3.371)	2.234*** (0.414)
LagAmihud5							0.019 (0.020)
Size	-0.001*** (0.000)	0.059*** (0.008)	0.102 (0.129)	67.540*** (9.923)	0.153 (0.145)	0.924*** (0.338)	0.028* (0.016)
Inst	0.000*** (0.000)	-0.004*** (0.001)	0.009** (0.004)	-0.625*** (0.128)	-0.013*** (0.005)	-0.013 (0.010)	0.000 (0.001)
Follow	-0.000 (0.000)	-0.000 (0.000)	0.001* (0.000)	-0.010 (0.095)	-0.003 (0.002)	0.013 (0.009)	-0.000* (0.000)
Mtb	-0.014*** (0.002)	0.065 (0.051)	-0.127 (0.248)	-109.420*** (17.385)	-1.064*** (0.398)	1.184** (0.563)	0.018 (0.055)
Roa	0.038*** (0.006)	-0.644*** (0.129)	0.085 (0.475)	-110.417*** (14.396)	0.471 (0.522)	-0.144 (0.818)	-0.065 (0.058)
Tobinq	-0.001*** (0.000)	0.009 (0.006)	0.022** (0.011)	-1.458 (1.799)	-0.085* (0.044)	0.187* (0.112)	0.016** (0.007)
Constant	0.047*** (0.009)	-1.868*** (0.187)	-4.159*** (0.790)	110.317*** (35.258)	-0.192 (1.342)	61.049*** (2.280)	-0.199 (0.125)
Observations	2,746	2,746	2,746	2,746	2,746	2,746	2,746

R-squared	0.033		0.040	0.062	0.047	0.026	0.027
Pseudo R2		0.064					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Panel B: Indirect Evidence (Size Matched)							
Dum_manip	-0.031*** (0.001)	0.799*** (0.071)	0.262*** (0.020)	-3.079*** (0.763)	0.718*** (0.071)	-2.894*** (0.694)	0.027*** (0.006)
Price	-0.003*** (0.000)	0.078*** (0.008)	-0.377*** (0.003)	24.333*** (4.964)	-0.458*** (0.017)	6.913*** (1.383)	0.022*** (0.001)
Lagturnover	-0.085*** (0.002)	0.440*** (0.155)	24.839*** (0.700)	-28.684 (243.057)	23.872*** (0.501)	-78.910 (74.096)	0.685*** (0.045)
Intravol	-0.000*** (0.000)	-0.005*** (0.001)	0.006*** (0.001)	-0.225 (0.182)	-0.016*** (0.004)	-0.006 (0.073)	0.000 (0.000)
Lagvol	0.051*** (0.004)	-2.777*** (0.411)	-3.213*** (0.289)	894.638 (698.782)	12.801*** (0.947)	375.339 (281.064)	-0.370*** (0.044)
Absret			1.555*** (0.366)	626.320*** (107.516)	32.419*** (4.418)	15.753*** (5.002)	1.079*** (0.325)
LagAmihud5							0.029*** (0.006)
Size	0.000*** (0.000)	0.001 (0.006)	0.073*** (0.009)	16.052** (7.857)	0.327*** (0.017)	0.627*** (0.135)	0.023*** (0.001)
Inst	0.000*** (0.000)	-0.000 (0.001)	0.010*** (0.000)	-0.271** (0.105)	-0.006*** (0.001)	-0.041 (0.030)	-0.000*** (0.000)
Follow	0.000*** (0.000)	-0.003*** (0.000)	0.004*** (0.000)	0.131* (0.074)	-0.002*** (0.000)	0.045** (0.020)	-0.000*** (0.000)
Mtb	-0.011*** (0.000)	0.131*** (0.044)	0.124*** (0.013)	-35.816 (25.527)	-1.423*** (0.039)	2.924*** (0.784)	-0.017*** (0.003)
Roa	0.030*** (0.001)	-1.147*** (0.105)	0.522*** (0.020)	-64.941 (52.614)	0.319*** (0.053)	-1.162 (0.811)	-0.059*** (0.004)
Tobinq	0.000*** (0.000)	-0.004 (0.007)	0.032*** (0.001)	-3.303* (1.858)	-0.070*** (0.005)	-0.100 (0.191)	0.005*** (0.001)
Constant	0.012*** (0.001)	-0.225* (0.120)	-2.177*** (0.032)	205.416*** (36.659)	-5.584*** (0.077)	73.838*** (3.651)	-0.150*** (0.009)
Observations	470,111	470,111	470,111	470,111	470,111	470,111	470,111
R-squared	0.008		0.053	0.025	0.023	0.019	0.012
Pseudo R2		0.006					



Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Panel C: Direct Evidence (Return Matched)							
Dum_manip	-0.016* (0.009)	0.212*** (0.051)	0.469* (0.249)	-3.206*** (1.001)	3.334*** (1.170)	-1.426*** (0.362)	0.019*** (0.003)
Price	-0.003*** (0.001)	0.153*** (0.017)	-0.286*** (0.021)	15.445*** (1.086)	0.308 (0.235)	5.386*** (0.164)	0.086** (0.036)
Lagturnover	-0.163*** (0.022)	0.740*** (0.204)	13.200*** (2.206)	83.803*** (24.616)	10.332*** (2.722)	22.573*** (2.554)	1.183** (0.549)
Intravol	-0.000*** (0.000)	0.007*** (0.000)	-0.003*** (0.001)	-0.027 (0.026)	-0.049*** (0.005)	0.109*** (0.004)	-0.001*** (0.001)
Lagvol	-0.008 (0.009)	0.099 (0.125)	-0.914 (0.802)	80.831*** (25.832)	0.846 (3.038)	10.681*** (2.526)	-0.405 (0.354)
Absret			8.348*** (1.393)	572.513*** (33.697)	107.567*** (10.482)	27.387*** (3.925)	4.707*** (0.739)
LagAmihud5							-0.004** (0.002)
Size	0.003*** (0.001)	-0.010 (0.013)	-0.026 (0.050)	8.433*** (1.416)	1.314*** (0.319)	0.923*** (0.159)	0.068*** (0.016)
Inst	0.000 (0.000)	-0.002 (0.001)	0.006*** (0.001)	-0.091*** (0.024)	-0.039*** (0.010)	-0.003 (0.006)	-0.000 (0.001)
Follow	-0.000*** (0.000)	-0.001 (0.001)	-0.002** (0.001)	0.036*** (0.009)	-0.009** (0.004)	0.017*** (0.003)	-0.000 (0.001)
Mtb	-0.022*** (0.005)	0.182** (0.079)	0.230 (0.163)	-9.881*** (2.666)	-3.570*** (0.945)	2.086*** (0.448)	0.024 (0.068)
Roa	0.056*** (0.013)	-0.650*** (0.203)	0.606 (0.498)	-21.040*** (4.779)	1.166 (1.759)	-4.033*** (0.865)	-0.344* (0.199)
Tobinq	-0.002** (0.001)	0.004 (0.009)	0.042*** (0.008)	-0.200 (0.412)	-0.290*** (0.097)	0.145*** (0.049)	0.010 (0.011)
Constant	-0.046** (0.019)	-0.486 (0.311)	-5.572*** (0.755)	166.933*** (5.500)	5.616 (3.604)	68.389*** (1.139)	-0.473*** (0.235)
Observations	2,046	2,046	2,046	2,046	2,046	2,046	2,046
R-squared	0.049		0.145	0.070	0.088	0.066	0.027
Pseudo R2		0.078					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Panel D: Indirect Evidence (Return Matched)							
Dum_manip	0.037*** (0.006)	0.269*** (0.077)	1.037** (0.413)	-1.475*** (0.428)	3.954*** (0.549)	-1.496*** (0.233)	0.131** (0.053)
Price	-0.028*** (0.001)	0.283*** (0.013)	-0.975*** (0.190)	13.258*** (0.805)	0.719** (0.331)	5.013*** (0.138)	0.669*** (0.102)
Lagturnover	-0.350*** (0.016)	-1.221*** (0.157)	127.437*** (17.356)	30.568** (12.004)	19.423*** (4.947)	13.753*** (1.598)	11.145*** (2.223)
Intravol	-0.000*** (0.000)	0.007*** (0.000)	0.017** (0.007)	-0.007 (0.033)	0.003 (0.003)	0.123*** (0.006)	0.002*** (0.001)
Lagvol	0.115** (0.050)	-3.597*** (0.341)	-110.873*** (14.650)	32.751* (17.593)	-338.707*** (24.758)	3.290* (1.906)	-37.858*** (3.346)
Absret			2.230 (2.236)	516.664*** (42.111)	66.615*** (3.779)	21.351*** (1.894)	7.504*** (0.748)
LagAmihud5							0.092* (0.052)
Size	0.004*** (0.001)	-0.046*** (0.010)	1.536*** (0.294)	5.212*** (1.103)	4.296*** (0.428)	0.386*** (0.056)	0.213*** (0.062)
Inst	0.000 (0.000)	-0.003*** (0.001)	0.031*** (0.008)	-0.011 (0.016)	-0.200*** (0.017)	0.002 (0.005)	-0.004** (0.002)
Follow	0.000*** (0.000)	0.000 (0.000)	0.040*** (0.006)	0.019* (0.010)	0.032*** (0.006)	0.019*** (0.002)	-0.003* (0.001)
Mtb	0.004 (0.005)	0.186*** (0.063)	-2.511*** (0.670)	-4.717 (2.971)	-2.375** (1.114)	2.880*** (0.265)	0.639** (0.282)
Roa	0.149*** (0.011)	0.344*** (0.126)	0.495 (0.877)	-13.384*** (3.891)	5.819*** (2.045)	-4.023*** (0.851)	0.536 (0.373)
Tobinq	-0.001** (0.001)	-0.000 (0.006)	0.036 (0.027)	-0.280 (0.272)	-0.703*** (0.091)	0.072* (0.042)	0.061* (0.034)
Constant	0.001 (0.020)	0.580** (0.243)	-7.854*** (2.348)	148.846*** (2.229)	95.955*** (7.328)	65.510*** (0.833)	-1.020 (0.824)
Observations	839,069	839,069	839,069	839,069	839,069	839,069	839,069
R-squared	0.127		0.129	0.249	0.187	0.182	0.091
Pseudo R2		0.051					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Panel E: Direct Evidence (Industry Matched)							

Dum_manip	-0.027*** (0.009)	0.437* (0.223)	0.947*** (0.202)	-1.170*** (0.376)	1.561* (0.889)	-1.888*** (0.390)	0.063*** (0.007)
Price	-0.006** (0.003)	0.168*** (0.055)	-0.243*** (0.030)	12.047*** (0.452)	-0.597*** (0.133)	4.913*** (0.228)	0.284 (0.315)
Lagturnover	-0.049 (0.066)	-0.506 (0.826)	6.084*** (1.159)	24.280*** (6.836)	5.473 (4.626)	12.332*** (1.836)	-2.622 (4.096)
Intravol	0.000*** (0.000)	0.002 (0.002)	0.002 (0.002)	-0.020 (0.031)	-0.005 (0.008)	0.119*** (0.012)	0.012 (0.010)
Lagvol	0.276** (0.123)	-0.490 (2.118)	-0.164 (2.210)	52.788*** (17.930)	3.021 (10.411)	15.874** (7.242)	-15.656 (12.975)
Absret			5.192*** (1.735)	528.239*** (29.574)	19.626*** (7.360)	34.866*** (6.748)	7.603* (3.959)
LagAmihud5							-0.125 (0.179)
Size	-0.003 (0.002)	0.089** (0.043)	-0.161*** (0.035)	5.056*** (0.604)	-0.494*** (0.152)	0.595*** (0.151)	-0.021 (0.067)
Inst	0.001*** (0.000)	-0.011** (0.004)	0.007*** (0.002)	-0.014 (0.018)	0.011 (0.011)	0.009 (0.007)	-0.008 (0.009)
Follow	0.000 (0.000)	-0.001 (0.002)	0.000 (0.001)	0.011 (0.008)	0.000 (0.005)	0.016*** (0.002)	0.001 (0.002)
Mtb	-0.019* (0.011)	-0.048 (0.258)	0.414** (0.179)	-4.649*** (1.336)	0.736 (0.795)	2.736*** (0.309)	0.457 (0.494)
Roa	0.027 (0.035)	-0.666 (0.617)	0.178 (0.364)	-7.227*** (2.490)	-1.802 (1.531)	-3.965*** (0.863)	-0.455 (0.647)
Tobinq	-0.000 (0.001)	-0.003 (0.027)	0.041* (0.024)	-0.353* (0.185)	0.150 (0.094)	0.093* (0.053)	0.061 (0.054)
Constant	-0.040 (0.047)	-1.146 (1.137)	-3.272*** (0.688)	144.449*** (2.192)	-11.221*** (3.492)	64.326*** (1.269)	0.368 (0.728)
Observations	2,046	2,046	2,046	2,046	2,046	2,046	2,046
R-squared	0.108		0.585	0.416	0.402	0.377	0.045
Pseudo R2		0.232					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Panel F: Indirect Evidence (Industry Matched)							
Dum_manip	-0.010*** (0.002)	0.510*** (0.007)	0.065* (0.036)	-3.501** (1.617)	0.762*** (0.190)	-0.998** (0.437)	0.018*** (0.005)

Price	-0.004*** (0.000)	0.145*** (0.002)	-0.422*** (0.011)	10.473*** (0.334)	-0.221*** (0.032)	4.789*** (0.219)	0.019*** (0.002)
Lagturnover	-0.099*** (0.002)	0.132*** (0.029)	28.489*** (1.584)	28.431*** (7.492)	17.127*** (0.830)	15.195*** (2.089)	0.503*** (0.069)
Intravol	-0.000*** (0.000)	0.003*** (0.000)	0.015*** (0.002)	-0.005 (0.023)	-0.011 (0.007)	0.099*** (0.013)	0.001*** (0.000)
Lagvol	0.076*** (0.014)	-0.195*** (0.058)	-4.101*** (0.799)	30.459** (13.060)	22.414*** (3.490)	8.445*** (3.241)	-0.502*** (0.112)
Absret			2.137** (0.844)	472.817*** (20.660)	48.472*** (14.239)	43.854*** (15.407)	0.842*** (0.311)
LagAmihud5							0.028** (0.013)
Size	0.001*** (0.000)	0.005*** (0.001)	0.194*** (0.024)	4.134*** (0.449)	0.498*** (0.038)	0.754*** (0.255)	0.021*** (0.002)
Inst	0.000*** (0.000)	-0.002*** (0.000)	0.013*** (0.001)	-0.031** (0.014)	-0.006*** (0.002)	0.011 (0.012)	-0.000*** (0.000)
Follow	0.000*** (0.000)	-0.001*** (0.000)	0.002*** (0.000)	0.024*** (0.006)	-0.001*** (0.000)	0.012*** (0.004)	-0.000*** (0.000)
Mtb	-0.014*** (0.000)	0.243*** (0.009)	-0.152*** (0.041)	-1.917 (1.603)	-1.068*** (0.075)	2.269** (0.987)	-0.006 (0.007)
Roa	0.038*** (0.001)	-0.523*** (0.019)	0.183*** (0.042)	-6.911 (6.220)	0.066 (0.114)	-3.884*** (0.882)	-0.033*** (0.007)
Tobinq	-0.000 (0.000)	0.005*** (0.001)	0.024*** (0.003)	0.121 (0.362)	-0.123*** (0.009)	0.179 (0.143)	0.003** (0.001)
Constant	-0.002 (0.002)	-0.881*** (0.042)	-4.568*** (0.142)	138.050*** (2.674)	-4.432*** (0.347)	58.162*** (1.215)	-0.100*** (0.019)
Observations	796,090	796,090	796,090	796,090	796,090	796,090	796,090
R-squared	0.013		0.050	0.041	0.029	0.026	0.014
Pseudo R2		0.015					
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Notes: Table M presents our baseline results using different matching methods. In Panel A and Panel B, we match treatment group and control group with firm size. In Panel C and Panel D, we match treatment group and control group with stock return of the previous trading day. In Panel E and Panel F, we match treatment group and control group with industry. Panel A, Panel C and Panel E report empirical results based on direct evidence. Panel B, Panel D and Panel F report empirical results based on indirect evidence. The dependent variable in column (1) is cumulative abnormal return ( $\Delta$ ). The dependent variable in column (2) is price reversal ( $\Delta$ ). The dependent variable in column (3) is abnormal turnover on the manipulation day ( $\Delta$ ). The dependent variable in column (4) is Amihud ratio on the manipulation day ( $\Delta$ ). The dependent variable in column (5)

is 5-day cumulative abnormal turnover after manipulation (). The dependent variable in column (6) is Amihud ratio after manipulation (). The dependent variable in column (7) is idiosyncratic volatility (). All regressions include year fixed effects and industry fixed effects. The detailed definition of control variables is shown in Appendix B. \*, \*\*, \*\*\* denotes 10%, 5%, and 1% levels of statistical significance, respectively.