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ABSTRACT

We identify a group of "suspicious" firms that use stock splits, perhaps along with other activities, to artificially inflate their share prices. Following the initiation of suspicious splits, share prices temporarily increase, and subsequently decline below their presplit levels. Using account level data from the Shanghai Stock Exchange, we find that small retail investors acquire shares in firms initiating suspicious splits, while more sophisticated investors accumulate positions before suspicious split announcements and sell in the postsplit period. We also find that insiders sell large blocks of shares and obtain loans using company stock as collateral around the initiation of suspicious splits.

1. Introduction

Under the guidance of academics and industry practitioners, China's stock market was launched in December 1990. By 2015, it was the second largest in the world by market capitalization. While its growth has been impressive, young burgeoning stock markets have been vulnerable to episodes of price manipulation. From the bear raids in the Amsterdam stock market in the seventeenth century, to the market corners and trading pools on Wall Street in the nineteenth and early twentieth centuries, regulators have fought to stay ahead of manipulators and struggled to restore stability and trust to financial markets.[1] Yet, such lessons appear to be hard to learn and are easily forgotten. As developing economies globalized in the late twenty-first century, price manipulation was a common occurrence in many emerging financial markets (e.g., Khanna and Sunder, 1999; Khwaja and Mian, 2005).

This paper examines whether Chinese firms are able to manipulate their share prices by taking misleading corporate actions. Two factors make the Chinese market particularly susceptible to such behavior. First, retail investors dominate trading and account for nearly 90% of daily trading volume on the Shanghai Stock Exchange (SSE).[2] Small retail investors tend to be relatively unsophisticated: approximately one third of all Chinese retail investors lack a high school education and a 2014 survey reports that the majority of new account openings were by investors who did not have a high school degree (Gan, Yin, and Tan, 2015). Second, short selling in the Chinese A-share market is substantially limited. Short selling was banned prior to 2010 and 2016 restrictions prohibited the short selling of nearly 70% of stocks. These short-selling restrictions prevent arbitrageurs from stepping in to counteract manipulative actions.

[1] See, for example, Allen and Gale (1992) and Jarrow (1992).
[2] The author's calculation is based on complete account trading data from the SSE during 2013 to 2015.

In this paper, we focus on how corporate insiders use stock splits, in combination with other activities, to artificially inflate their share price. In many regards, stock splits provide an ideal corporate vehicle for manipulation. Given that these announcements attract considerable attention, insiders have an incentive to split their shares when they have favorable information to convey. As discussed in Grinblatt, Masulis, and Titman (1984) and Almazan, Banerji, and de Motta (2008), splits can be credible signals in fully rational models because the increased scrutiny associated with stock splits can be costly for firms with unfavorable private information. However, in a market dominated by unsophisticated retail investors and in the presence of short sale constraints, splits can temporarily inflate a firm's stock price. Unsavory insiders with short horizons or immediate capital needs may use this opportunity to sell shares or benefit in other ways. Our notion of manipulating with splits is consistent with Benabou and Laroque (1992), who provide a model in which insiders with noisy private information make biased public announcements to manipulate stock prices.

Stock manipulation is illegal and fraudulent under Chinese securities law (Article 77). A recent investigation by the Chinese Securities and Regulatory Commission (CSRC), which is the equivalent of the U.S. Securities and Exchange Commission, reveals that stock splits are a common tactic used by manipulators to draw in retail investor interests.[3] The criminal and civil penalties are costly. In a high-profile court case, Xiang Xu, the hedge fund manager of the Zexi Investment Company, was sentenced to a five-and-half-year jail term and paid a fine of 11 billion Chinese yuan for conspiring with managers to announce splits and simultaneously conduct wash trades

[3] China Securities Regulatory Commission, 2018. Report on market manipulation cases in the first half of 2018. Available at: www.csrc.gov.cn/pub/newsite/jcj/gzdt/201808/t20180813_342582.html.

using unaffiliated trading accounts. Our analysis reveals that the use of stock splits in the Xiang Xu scandal was not an isolated incident. [4]

We start by using ex ante information to identify a sample of splits across both the Shanghai and Shenzhen stock exchanges that might raise suspicion based on the unusual circumstances surrounding their announcements. Although the information used to identify these "suspicious" splits was publicly available at the time of the split announcement, it is doubtful that Chinese retail investors were equipped to access and interpret these warning signs. This sample of suspicious splits excludes those made by state-owned enterprises (SOEs) because their government-appointed executives tend to have strong political career incentives that make it very costly to engage in manipulating their stock prices.[5]

From this sample of non-SOEs, we further stratify the sample based on characteristics that are likely to be associated with a higher probability that insiders are colluding to artificially boost their share price. First, we investigate stock split announcements made outside of traditional split announcement periods or after poor recent stock performance. The latter announcements are suspicious because a common rationale for stock splits is to restore the stock price to an optimal trading range, usually after a period of strong price appreciation (Baker and Gallagher, 1980). Second, we identify firms that concurrently announce a stock split and report high accruals, which can be associated with earnings manipulation (Teoh, Welch, and Wong, 1998a, 1998b; Piotroski

[4] We perform a case study of the split events uncovered in the investigation and report our findings in the Internet Appendix.

[5] Fan, Wong, and Zhang (2007), Wong (2014), and Cao, Lemmon, Pan, Qian, and Tian (2019) discuss the tendency of SOE executives to avoid controversial activities because of their focus on competing to move up the internal political ranking system. SOE executives also have significantly less equity ownership in their firms. Chen, Guan, and Ke (2013) find that managers at SOEs either never exercise their stock options or exercise them but leave the firm and the political tournament system. We find no evidence of manipulation around stock split announcements of SOEs.

and Wong, 2012).[6] Finally, we conjecture that insiders with particularly strong incentives for their share price to be temporarily high (Spatt, 2014) will use stock splits to manipulate the short-term share price. Specifically, we collect data on the impending lock-up expirations of shares with trading restrictions held by influential shareholders (i.e., larger shareholders and institutional investors) that occur in the months surrounding the stock split announcement date.

Figure. 1 illustrates our main findings. The returns following suspicious splits exhibit an inverse U-shaped abnormal return pattern. The buy-and-hold size-adjusted returns of suspicious splits have a positive 10% run-up by the third month after the split announcement, but reverse back to the presplit level within 18 months.

The initial positive return followed by a subsequent reversal is a distinguishing feature that separates market manipulation from other opportunistic behavior. For example, nonsuspicious splits also experience an initial positive market reaction and a modest upward drift, but no subsequent reversal. The postannouncement behavior of the nonsuspicious splits mirrors the evidence in the United States and is suggestive of *underreaction* to corporate announcements (Daniel, Hirshleifer, and Subrahmanyam, 1998).[7] The timing of these splits may be opportunistic in that they may reflect the timing of option grants and anticipated insider trades (Devos, Elliot, and Warr, 2015). However, the lack of return reversals indicates that the initial price appreciation was permanent and therefore unlikely to reflect market manipulation.

Additional tests provide evidence of a relation between retail investor attention and the temporary price appreciation and reversal patterns among suspicious splits. We observe more

[6] See Teoh, Welch, and Wong (1998a, 1998b) for U.S.-based evidence and Piotroski and Wong (2012) for China-based evidence.

[7] See, for example, Grinblatt, Masulis, and Titman (1984), Ikenberry and Ramnath (2002), and Chan, Li, and Lin (2019). We also verify that the positive abnormal post-announcement drift occurs among U.S. stocks during our 1999–2015 sample period (see Figure. 1).

extreme postannouncement returns of suspicious splits for small capitalization stocks and splits that drop the nominal price level below $10. These conditional patterns are consistent with the observed retail preference for small stocks and stocks with low nominal price levels (Lee, Shleifer, and Thaler, 1991; Kumar and Lee, 2006). Moreover, following Hirshleifer, Jian, and Zhang (2018), we examine the suspicious splits of firms with "unlucky" listing codes because there is evidence that some retail investors avoid these stocks because of numerological superstition. Among these "unlucky" suspicious splits, there are no significant run-up and reversal patterns.

For direct evidence on the buyers of suspicious splits, we analyze proprietary trading records from the Shanghai Stock Exchange.[8] We find that small retail investors (accounts <=$5M Renminbi (RMB)) are attracted to stock splits unconditionally; their net buying significantly increases after the split announcement, representing about 450% of average daily volume over the following three months. They are strong net buyers of both suspicious and nonsuspicious splits after the split announcement, consistent with our conjecture that less sophisticated investors are unable to recognize the warning signs of suspicious firms. Interestingly, small retail investors significantly increase their net buying *before* the split announcement only for suspicious splits. In subsequent analysis, we explore whether information leakage can explain this behavior.

In contrast, large accounts (>$5M RMB) are net sellers after the split announcement and are particularly aggressive in selling suspicious splits. Large accounts appear to have private information about impending split announcements as they accumulate shares across all types of splits approximately one month before the public split announcement. While account identities are anonymized in our sample, our evidence mirrors recent findings that large accounts are informed and are suspected of belonging to corporate insiders (Chen, Gao, He, Jiang, and Xiong, 2019). The

[8] This sample constitutes 39% of the splits in our sample.

documented pattern of large individual investors buying before the announcement and selling shares back in the postsplit period is consistent with a sophisticated strategy of exploiting positive-feedback traders (De Long, Shleifer, Summers, and Waldmann, 1990; Pearson, Yang, and Zhang, 2021).

A detailed examination of account characteristics reveals that retail buyers of suspicious splits are likely to be less financially sophisticated (Calvet, Campbell, and Sodini, 2007, 2009; van Rooij, Lusardi, and Alessie, 2011). Buyers of suspicious splits have smaller account balances, opened their trading account more recently, and experienced worse return performance. Suspicious split buyers also tend to trade more, and are more likely to be male, which suggests that they can be more overconfident (Barber and Odean, 2000, 2001).

As mentioned earlier, since there are costs associated with using splits to falsely signal, insiders will engage in this activity only when the benefits are high. We examine the extent to which insiders and large shareholders use the opportunity of an inflated share price to unlock capital. Because of strict regulatory selling restrictions, insiders in China tend to use off-exchange transactions to relax financial constraints and circumvent detection by regulators.[9] We suspect that insiders sometimes collaborate with hedge funds and use split announcements to create favorable conditions for selling large blocks of shares off-exchange, thereby circumventing the shareholder selling restrictions. Consistent with our hypothesis, block trades are more likely to occur around the announcement of suspicious splits with impending lock-up expirations. However, there is no significant association between block trades and split announcements, unconditionally. We also

[9] We focus on off-exchange transactions for the following reasons: 1) shareholders with significant holdings are prohibited from selling more than 1% of company shares in a three-month period on the exchange directly, 2) Chinese regulators heavily scrutinize direct on-exchange trades by corporate insiders and influential large shareholders, and 3) regulation requires shareholders with significant holdings to report their intent to trade at least 15 trading days in advance if they plan to sell on the secondary market.

suspect that insiders and large shareholders use split announcements to temporarily inflate their stock price for the purpose of obtaining stock pledges loans. Because these are equity-backed loans collateralized by shares, insiders can secure larger loans when their share price is high. We find a significant increase in the percentage of share pledge loans immediately around the announcement of suspicious splits that concurrently report a high level of accruals.

Our manipulation story implies that insiders *intentionally* inflate their share price, but an alternative view is that investors simply mis-value splits (Birru and Wang, 2016). While this interpretation is difficult to rule out, news articles report anecdotes and anonymous tips that document the use of stock splits to facilitate the selling of shares by insiders (see Appendix C). To provide evidence on another potential manipulation channel, we obtain a sample of message board postings on the popular Eastmoney Guba stock forum. Estimates from Poisson regressions reveal significant increases in message board activity in the two weeks before the announcement of a suspicious split. Although the evidence is circumstantial, it is consistent with a concerted "pump and dump" effort that uses splits along with other questionable activities.

Finally, we note that stock splits are endogenous corporate actions that tend to occur along with earnings releases, dividend choices, and other announcements. As such, we cannot say that stock splits per se are the sole manipulation instrument, only that they are one tool in the toolkit of manipulators. We can, however, roughly gauge the influence of stock splits on retail investors relative to that of the suspicious characteristics, earnings news, and dividend announcements. To do this, we first calculate alternative excess returns around suspicious split announcements by matching the suspicious splits to a sample of nonsplit firms of a similar size that also exhibited the same suspicious characteristic, experienced comparable earnings surprises, or made a dividend announcement. These alternative benchmarks produce a similar and sometimes larger inverse U-shaped abnormal return pattern, suggesting that our findings do not simply reflect the suspicious characteristics, concurrent earnings surprises, or dividend actions. Second, we examine the full sample of trading account records for all stocks on the SSE from 2013 to 2015 and find that while retail investors are significantly more likely to purchase split announcers, they did not significantly increase buying in a matched sample of nonsplit firms that were similar in size and experienced similar changes in earnings. We further examine the possibility that dividend announcements could also capture the attention of retail investors; however, the announcement of periodic dividends or dividend increases does not generate significant announcement returns. Also, trading account records reveal that retail investors did not significantly increase buying in dividend announcers compared to a matched sample of firms with similar stock price reactions to earnings announcements and past returns. Overall, it seems that stock splits are special: they attract the attention of retail investors more often than these other corporate actions.

The analysis in this paper contributes to a growing literature on manipulative behavior in developed and less developed markets.[10] A key feature of market manipulation is a predictable pattern of price reversal. For example, Khwaja and Mian (2005) examine the trading records of brokers in the Pakistan stock exchange and identify wash trades that generate temporary price appreciation and reversal patterns. In the U.S. market, the manipulation of closing prices from "pegging" and "leaning for the tape" activities also generate predictable reversals.[11] In China, Chen, Gao, He, Jiang, and Xiong. (2019) find strong evidence of manipulation around price

[10] Putniņš (2012) and Spatt (2014) provide recent reviews of the stock manipulation literature. There are also studies that evaluate known manipulation cases to understand the characteristics of manipulation (e.g., Aggarwal and Wu, 2006; Allen, Litov, and Mei, 2006; Comerton-Forde and Putniņš, 2011; Allen, Haas, Nowak, and Tengulov, 2019).

[11] See, for example, Carhart, Kaniel, Musto, and Reed (2002), Ni, Pearson, and Poteshman (2005), and Golez and Jackwerth (2012).

limits.[12] They show that large investors trade aggressively to push up prices to hit the trading limit so as to sell afterwards at higher prices to naïve retail investors. Our focus on corporate actions that contribute to manipulation distinguishes our research from the existing work. Using ex ante information, we identify a group of firms that initiate splits under suspicious circumstances and show that these stocks subsequently experience temporary price appreciation and reversal.

Our paper also adds to growing international evidence on the use of stock splits. Concurrent papers have also found positive market reactions to split announcements in China (Fang, Hu, and Wang, 2015; Cui, Li, Pang, and Xie, 2019). In Vietnam's market, Nguyen, Tran, and Zeckhauser (2017) find positive market reactions and heightened volume around split announcements, which they argue is consistent with illegal insider trading. In contrast, we focus on the postannouncement period and show temporary price appreciation and reversal among suspicious splits.[13] Although the evidence on suspicious splits is in contrast to the U.S. evidence of underreaction to stock splits and other corporate announcements, the postsplit behavior of the nonsuspicious splits closely resembles the U.S. evidence described in Ikenberry and Ramath (2002).[14]

2. Sample, data, and summary statistics

We obtain daily stock return and split announcement data for China A-shares from the China Stock Market and Accounting Research (CSMAR) database.[15] Our sample starts in January of

[12] These price effects can result from margin trading (e.g., Bian, Da, Lou, and Zhou 2017; Bian, He, Shue, and Zhou, 2017; Hansman, Hong, Jiang, Liu, and Meng, 2018) as well as investors' speculative motives (e.g., Mei, Scheinkman, and Xiong, 2009; Xiong and Yu, 2011).

[13] Related studies show that stock splits can act as a confirming signal of positive private information (Louis and Robinson, 2005) or can lead managers to undertake subsequent corporate actions to justify the split signal (Guo, Liu, and Song, 2008; Chan, Li, and Lin, 2019).

[14] Daniel, Hirshleifer, and Subrahmanyam (1998) provide a model in which overconfident investors underreact to corporate events, like stock splits.

[15] The Chinese stock market has institutional features similar to the U.S. markets. Both the Shanghai and Shenzhen markets are modern electronic systems without designated market makers. Buy orders are placed in round lots of 100 shares, but sell orders have no lot size requirements. The mean/median closing stock price as of December 2015 is $17.99/$24.32RMB ($2.76/$3.73USD) in our sample. The maximum price is $218.19RMB ($33.50USD). Therefore, it is unlikely that round lot constraints would affect most investors.

1999; the Chinese stock market is relatively undeveloped before then, and we are less confident about the accuracy of the pre-1999 data. Our sample of split announcements ends in June 2015 and our analysis of postsplit announcement stock returns ends in December 2016. The splits are typically proposed in the annual report (92% of the sample) because they require shareholder approval.[16] In theory, since splits can be withdrawn, the content and ex-dates could convey information. However, 99.7% of the splits announced in our sample period were approved.

We start with a sample of 4,510 stock split announcements that have complete accounting information and at least one year of prior stock returns included in the CSMAR database. Chinese firms issue two types of splits, stock dividends and stock transfers, which are technically the same and have no impact on a firm's earnings or operations (He, Li, Shi, and Twite, 2016).[17] Following prior event studies of the China market (e.g., Liu, Shu, and Wei, 2017), we screen out stock splits that fail to report trading in the three-day window around the split announcement date. This approach eliminates confounding events, such as trading halts that occur around information-sensitive events. We also exclude stocks with abnormal financial conditions designated as "special treatment" (code ST or ST-plus) or "particular transfer" (code PT) by the stock exchange because these stocks face trading and financial restrictions (Peng, Wei, and Yang, 2011).[18] Our sample consists of 3,716 stock splits after implementing these screens.

As we discussed in the introduction, our analysis of manipulation focuses on firms that are not state owned. We classify a firm as an SOE if the ultimate owners are the Chinese government.

[16] Approximately two weeks later, the results are revealed on the content date; if approved, the ex-date is disclosed.

[17] The difference between stock dividends and stock transfers is in the accounting treatment. Stock dividends are issued from shareholder equity while stock transfers are issued from the capital reserve fund. Eighty-four percent of the splits in our sample are performed using stock transfers.

[18] The stock exchange carefully monitors the performance of special treatment stocks by auditing the interim company reports of ST-status stocks, imposing a +/− 5% daily price limit, and requiring investors who wish to trade ST stocks to sign a risk acknowledgement contract. The company faces delisting if it cannot return to profitability in the near future. Stocks designated particular transfer status are suspended from normal trading.

The definitions are provided by CSMAR, but only begin in 2002. If the Chinese government is the owner in 2002, we assume that it was also the owner in the prior three years of our sample. We also classify a firm as an SOE if it has received debt financing from the Chinese government. Otherwise, we classify the firm as a non-SOE. We are intentionally conservative in classifying firms as non-SOEs to avoid identifying false positive suspicious splits.[19]

To better understand the motives of the insiders who announce suspicious splits, we examine some of their capital-raising activities. We gather off-exchange block trade transaction data (2002/01 to 2015/12) from CSMAR, and share issuance and share pledge loan data (2006/01 to 2015/12) from the WIND database. The share issuance database reports the share type (e.g., initial public offering (IPO), secondary equity offering (SEO), private placement, employee incentive plans, privatizations), share features (restricted, extra allotments, added promises, matched shares), owners of the shares (e.g., institutional investors, large shareholders, employees), and the date when the shares are tradable. Appendix A provides additional details of the block trades, share pledge loans, and shares with lock-up expirations used in this study.

We also collect a sample of message board postings from the Eastmoney Guba internet stock forum (guba.eastmoney.com) to explore a complementary channel for influencing retail investors. Eastmoney Guba is one of the largest and most active internet stock forums in China. Our sample starts in January 2010 and ends in April 2013, when the collection process stops. The sample collection process follows the same procedure used in Chang, Hong, Tiedens, Wang, and Zhao (2015). Our final sample contains 789,461 total postings and 1,410 stocks, which represents approximately 75% of all stocks listed on the Shanghai and Shenzhen stock exchanges during this period.

[19] Our results are not sensitive to using the CSMAR SOE classification. However, we note that the CSMAR classification changes annually.

2.1. Shanghai Stock Exchange trading data

We obtain the complete trading account records of stocks that announced stock transfers on the SSE from January 1999 through December 2015. The account data contains the security code, encrypted account identifier, trade price, trade volume, trade direction, and date and time of the trade. We also obtain a second sample of complete trading records of *all stocks* on the SSE for a three-year period from January 2013 through December 2015. We use this latter sample to analyze accounts characteristics in Section 5.2 and to perform additional robustness tests in Section 7.

The SSE classifies accounts into 12 types,[20] which we aggregate into the following four groups: *small retail* are retail investors with account wealth less than or equal to five million Chinese RMB; *large accounts* are investors with account wealth above five million Chinese RMB; *institutional investors* are mutual funds, broker asset-management companies, broker self-trading accounts, institutional investors, and insurance companies; and *other investors* include qualified foreign institutional investors and social security accounts. Our analysis of the complete SSE trading records (2013–2015) shows that retail investors dominate trading. Total retail investors (small + large) generate 89.1% of the total trading volume, mostly from small accounts (60.3%), consistent with findings in other samples of Chinese exchange trading data.[21]

We measure trading activity by creating a measure of net buying within each of the four investor groups following a similar approach used in Kaniel, Saar, and Titman (2008). For each stock *i*, on each day *t*, within each investor group *j*, we define net buying as:

[20] The 12 account types include five groups of individual retail accounts with wealth levels: i) less than 100,000 RMB, ii) between 100,000 and 1,000,000 RMB, iii) between 1,000,001 and 5,000,000 RMB, iv) between 5,000,001 and 10,000,000 RMB, and v) over 10,000,000 RMB. The remaining seven account types are mutual funds, broker asset management companies, broker self-trading accounts, insurance companies, general institutional investors, qualified foreign investors, and social security accounts.

[21] We provide summary statistics of trading volume by investor type in the Internet Appendix. Chen, Gao, He, Jiang, and Xiong (2019) also find that retail investors dominate trading in the Shenzhen market in a recent period.

$$Net\ Buy_{i,t,j} = \frac{\sum_{i,t,j} RMB\,Buy - \sum_{i,t,j} RMB\,Sell}{Average\,Daily\,Volume_{i,t-1,j}},$$

where *average daily volume* is the average daily volume (RMB) over the past trading year. For our analysis, we accumulate net buy over various windows for each investor group around split announcement dates.

2.2. Identifying suspicious splits

For the sample of non-SOEs that announce splits, we further classify firms as "suspicious" if their split announcement raises suspicion in some ways. Our classification is motivated by the unusual circumstances of the split announcement or based on academic studies that have shown related behavior that mislead investors. In total, approximately 21% of our split sample is classified as suspicious.

2.2.1. Suspicious splits: Lock-up expirations of shares held by influential shareholders

We conjecture that insiders or influential shareholders (i.e., large shareholders and institutional investors) who are seeking to exit their positions at more favorable prices can use splits to attract retail investor attention and liquidity. Indeed, the rumors of such activities were reported in the Chinese business press (Wang, 2013) and have come under regulatory scrutiny in recent years (Shen and Ruwitch, 2017). To identify potential insider exits, we focus on lock-up expirations of shares with trading restrictions (e.g., IPOs, SEOs, private placements, privatizations) held by influential shareholders that occur from month −1 to +6 around split announcements. We classify influential shareholders as institutional investors or shareholders holding shares with "added restrictions," "added promises," "matched shares," or "extra allotments." We suspect that shareholders who have strong influence over management are able to secure such favorable terms.

Shares with trading restrictions typically have a lock-up period of one year, but for management and controlling shareholders, the lock-up period is three years. While our choice of the lock-up expiration period surrounding the split announcement is somewhat arbitrary, our findings are similar when using lock-up expirations that occur from month −3 to +3 or from month −6 to +6. We also note that this sample represents *potential* shareholder exits, as these shareholders can continue to hold their shares and actual records of the specific trades of these shareholders are not available.

2.2.2. Suspicious splits: Atypical announcement timing

Managers typically split their shares after strong recent stock performance, but a set of firms in our sample announce stock splits after recent poor performance. We identify this category of suspicious splits by calculating the three-month stock return prior to announcement and identify split-announcing firms that reside in the bottom quintile of past three-month return. Our results are similar using the 15th percentile and 25th percentile of the past three-month return and are described in the Internet Appendix. [22] Another red flag is an announcement of a split at an unusual time. As discussed earlier, about 92% of the splits are announced concurrently with the earnings release. We categorize those splits announced outside of earnings announcement periods as suspicious.

2.2.3. Suspicious splits: High accruals

Our third category of suspicious split announcements includes firms that concurrently announce rosy accounting numbers as measured by high accruals (e.g., Teoh, Welch, and Wong, 1998a, 1998b; Piotroski and Wong, 2012). Specifically, we measure accruals as the difference

[22] To further assess the validity of this classification, we perform a falsification test by analyzing nonsuspicious splits that experience a high price run-up, defined as split-announcing firms that reside in the top quintile of the past three-month return. We observe no difference in the postannouncement abnormal returns for these splits compared to nonsuspicious splits that did not experience high price run-ups. The results are available in the Internet Appendix.

between operating income minus net cash flows from operations divided by total assets, following Liu, Shu, and Wei (2017). Our results are similar using accruals measured as the change in working capital minus depreciation (e.g., Sloan, 1996; Liu, Stambaugh, and Yuan, 2019).

2.3. Summary statistics

Table 1 reports summary statistics of the characteristics of firms that announce stock splits. For each month with a stock split announcement, we first calculate the average characteristics for stocks with and without a split announcement, and then report the time-series averages.

Panel A reports a comparison of split announcers to firms that did not announce splits in the same calendar year. Firms that announce splits have significantly larger market capitalizations, higher price levels, and greater analyst following. They do not differ significantly on measures of risk, such as beta or idiosyncratic volatility, nor on share turnover. Split announcers have significantly greater market reactions at the annual earnings announcement. While the majority of firms announce dividends, split announcers are somewhat less likely (−0.53%) to announce cash dividends compared to nonsplit announcers. Split announcers also exhibit stronger growth characteristics, such as significantly higher past three-month returns, higher return on assets (ROA), lower leverage, lower book-to-market ratios (BM), lower earnings-to-price ratios (EP), and higher accruals. They are less likely to be SOEs.

Panel B provides a comparison between suspicious split announcers and nonsuspicious split announcers. Suspicious splits have smaller market capitalizations than nonsuspicious splits but are similar on many other dimensions, including price level, analyst coverage, and turnover. On the risk dimension, suspicious splits have significantly lower betas but do not differ significantly from nonsuspicious split announcers in terms of idiosyncratic volatility. Suspicious split announcers also have lower BM and lower EP, but the differences are not economically large. By construction, the suspicious splits have lower past returns and higher accruals than their nonsuspicious counterparts. Overall, on observable dimensions of firm and stock characteristics, unsophisticated investors may not be able to distinguish between suspicious and nonsuspicious splits.

3. Price manipulation using stock splits

In this section, we explore the possibility that stock splits are used to manipulate share prices by analyzing market reactions around split announcements during the 1999 to 2015 sample period.

3.1. Market reaction to stock splits: Unconditional evidence

Table 2 reports the abnormal returns around stock split announcements for the full sample, SOEs, and non-SOEs. Our main analysis uses monthly data to calculate the buy-and-hold abnormal return (BHAR). We assess statistical significance using robust (White) standard errors that correct for the possible effects of events clustering during each calendar month. We also report abnormal returns around a shorter horizon using the daily BHAR during the three-day announcement window and the ten trading days before and after the split announcement.

The BHAR is calculated as the difference between each stock's buy-and-hold return minus the return of the corresponding size-decile value-weighted benchmark portfolio, matched at the prior December year-end. We choose return benchmarks based on size deciles because existing studies consistently find strong size effects, but there is an ongoing debate about the importance of other factors in the Chinese market (e.g., Hu, Chen, Shao, and Wang, 2019; Liu, Stambaugh, and Yuan, 2019; Li, Liu, and Wei, 2019; Carpenter, Lu, and Whitelaw, 2021). Our findings are robust using alternative return benchmarks (see Section 7).

Panel A of Table 2 reports the monthly BHAR. Unconditionally, stock splits exhibit three-month preannouncement abnormal returns of 4.75% (t=6.25). The magnitude of the return in this period is relatively small compared to what has been found in past studies in the U.S. market, which suggests that the motive for adjusting a firm's stock price back to a preferred trading range could be less important for stock splits in China. The abnormal return in the announcement month is 4.45% (*t*=13.98). As we will discuss shortly, this reflects the abnormal return around the announcement and the abnormal return run-up in the previous two weeks before the announcement. Over the next three months (+1 to +3), the all-split sample has a BHAR of 2.15% (*t*=3.31), which suggests that the price continues to drift upwards for up to three months. The drift is larger for non-SOE splits (2.99%, *t*=3.31) than SOE splits (1.43%, *t*=1.84). Return reversals occur among non-SOEs over the 15-month period from month +4 to +18 (−5.31%, *t*=−2.17), but not for SOEs (−0.05%, *t*=−0.03). The last column shows that over the entire year and half period, including the split month, the overall returns are significantly positive for the overall split sample (4.77%, *t*=3.11) and the SOE sample (5.81, *t*=3.45), but not for the non-SOE sample (3.55%, *t*=1.47).

In panel B of Table 2, we report daily excess returns in the period surrounding the splitannouncement. Unconditionally, stock splits have an abnormal return of 1.85% (*t*=13.62) in the three-day period around the announcement. The excess returns are larger for non-SOEs (2.04%, *t*=10.17) compared to SOEs (1.69%, *t*=10.68). Stock splits also exhibit large preannouncement run-ups from day −10 to −2 (2.66%, *t*=11.47), which are slightly larger for non-SOEs (2.88%, *t*=8.34) compared to SOEs (2.47%, *t*=11.80). These run-ups could reflect information leakage or, alternatively, management's tendency to choose to split shares only if the recent performance is favorable. The third column reports insignificant returns in the immediate two weeks after the announcement across all three samples.

3.2. Abnormal returns around suspicious splits

Our unconditional evidence does not support the hypothesis that splits, in general, are part of a pervasive manipulation scheme. If this were the case, we would observe significantly negative postsplit returns in the full sample of splits. We do find, however, relatively weak evidence of reversals among the splits of the non-SOEs, which suggests that there could be some manipulation within this group of firms. To consider this possibility more closely, we focus our upcoming analysis on splits that we have characterized as suspicious.

Table 3 reports monthly abnormal returns around the announcements of suspicious and regular non-SOE splits. Both samples exhibit significantly positive abnormal returns in the split announcement month of 5.69% (t=6.26) and 4.17% (t=7.77), respectively. We observe significantly positive abnormal returns over the subsequent three months for both the suspicious sample (3.26%, t=2.39) and the regular non-SOE sample (2.76%, t=3.77). However, the suspicious sample experiences a significantly negative and economically large reversal from month +4 to +18 of −10.99% (t=−3.40). In contrast, regular non-SOE splits do not experience abnormal returns over the same period (−0.47%, t=−0.14). Over the entire year and a half period that includes the split month, the abnormal returns for suspicious splits are not statistically distinguishable from zero; the positive abnormal returns that occurred during the announcement month and subsequent three-month period are fully reversed. In contrast, the regular non-SOE splits experienced a significantly positive abnormal return of 7.07% (t=2.13), which is consistent with the signaling hypothesis that these firms were undervalued at the time of their splits. Generally, regular non-SOE splits exhibit return patterns that are comparable to splits by SOEs, as reported in Table 2, panel A (bottom row).

Figure. 1 combines and presents the following four samples of splits: 1) suspicious splits (solid line), 2) regular non-SOE splits (dotted line), 3) SOE firms that announce splits (dashed line), and 4) U.S. firms that announce splits over the same sample period (dotted-dashed line).[23] Suspicious splits are the only group to experience return reversals after the initial positive drift.

[23] For the U.S. splits, the average BHAR is calculated as the buy-and-hold return minus the DGTW (Daniel, Grinblatt, Titman, and Wermers, 1997) benchmark (See the Internet Appendix for details).

The inverse U-shaped pattern is consistent with manipulation of the stock price through the use of splits.

Panel B of Table 3 reports results for each of the three characterizations of suspicious splits. The first row reports our analysis of suspicious splits with lock-up expirations. The market reacts favorably to the initial split announcement in month=0 (4.71%, t=3.69) and over the subsequent three months (4.72%, t=2.09). However, the excess returns become significantly negative from month +4 to +18 (−13.63%, t=−2.98). The second row reports our analysis of the sample of suspicious splits with atypical timing. The initial market reaction is positive in the month of the split announcement (6.10%, t=5.04) and subsequent three months (3.49%, t=1.86), but significantly negative from month +4 to +18 (−9.74%, t=−2.51). The third row of panel B reports our third category of suspicious split announcements, which is based on high accruals. We observe a pattern similar to the previous two types. After the significantly positive initial market reaction in the announcement month (5.35%, t=4.57), suspicious splits with high accruals experience excess returns in the subsequent three months of 2.92% (t=2.71) and a significantly negative reversal of −14.64% (t=−3.54) from month +4 to +18.

Overall, the inverse U-shaped pattern is prevalent whether viewed collectively as a group, or individually based on the suspicious characteristics.

3.3. Retail attention and suspicious splits

This section examines the relation between retail investor attention and the temporary price appreciation and reversal patterns among suspicious splits. We exploit heterogeneity in stock characteristics of suspicious splits that could attract additional retail interest. For example, retail investors have trading preferences for stocks with low market capitalization and low nominal price (Lee, Shleifer, and Thaler, 1991; Kumar and Lee, 2006). Moreover, it might be easier to manipulate the price of smaller capitalization stocks because they tend to be less liquid and are followed by fewer analysts.

Figure. 2 shows more extreme run-up and reversal patterns for suspicious splits that attract additional retail attention. Panel A plots the BHAR of low (high) market capitalization suspicious splits formed using the bottom 30th (top 70th) percentile of market capitalization based on previous quarter size breakpoints. We observe a much larger market reaction to split announcements for small firms (solid line) than for large firms (dashed line) as the initial cumulative abnormal return reaches 19% after the third month following the split announcement. The subsequent return reversal is also larger, as the abnormal return over the entire year and a half period falls below the original presplit risk-adjusted level (−7.1%). We find similar patterns when we characterize firms by double-sorting on both size and analyst coverage, which we report in the Internet Appendix.

Panel B plots the BHAR of suspicious splits that dropped the share price from above $10 to below $10 after the split. Our choice of $10 is somewhat arbitrary but is based on the salience of a double-digit number and the median stock price during our sample period ($9.60). We separately track suspicious splits whose postsplit price remained above $10 as a comparison. For "postsplit < $10" (solid line) split announcers, we observe large initial market reactions and subsequent reversals. The initial cumulative abnormal return reaches 14% after the third month following the split announcement before reversing and falling below the original presplit risk-adjusted level. In contrast, "postsplit price >=$10" split announcers (dashed line) experiences a 6.4% run-up in the first three months before experiencing a modest reversal and remains above its presplit risk-adjusted level after 18 months.[24]

Next, we design a test to exploit the reduced retail interest in stocks with "unlucky" listing codes. Hirshleifer, Jian, and Zhang (2018) find that numerological superstition affects stock returns in the China A-shares market. Specifically, newly listed firms with lucky stock listing codes experience poor post-IPO abnormal returns in the secondary market relative to stocks with unlucky listing codes. Their results imply that the mispricing of lucky listing codes is due to unsophisticated investors, who base their portfolio selection on numerological superstition. For similar reasons, we expect retail investors to avoid suspicious splits with unlucky listing codes, which would make these stocks more difficult to manipulate. We identify unlucky listing codes as those containing the unlucky digit 4, but not any of the lucky digits 6, 8, or 9 following the classification system in Hirshleifer, Jian, and Zhang (2018). We focus on unlucky listing codes because nearly half of the suspicious splits have lucky listing codes (i.e., codes that contains one of the lucky digits 6, 8, or 9, but not the unlucky digit 4).[25]

Panel C plots the BHAR of unlucky versus not-unlucky suspicious splits. For suspicious splits with unlucky listing codes (dotted line), we do not observe positive drift after the initial reaction to the split announcement. In contrast, the other listing codes (solid line) exhibit positive run-up and subsequent return reversal patterns. The evidence is consistent with the view that retail investors avoid suspicious splits with unlucky listing codes. The implication is that without these

[24] To ensure that these patterns are not a manifestation of large/small stock effects in panel A, we limit the sample to only large stocks. We continue to observe a similar pattern, which suggests that the results are not due to possible sorting on small stocks. These results are available in the Internet Appendix.

[25] The frequency of lucky numbers in a suspicious split sample is comparable to the sample analyzed in Hirshleifer, Jian, and Zhang (2018), where 60% of stocks have lucky listing codes.

investors, managers are unable to manipulate their shares using corporate actions such as stock splits.

Overall, the evidence indicates that retail attention is an important ingredient in market manipulation. The results indirectly imply that uninformed and possibly less financially sophisticated investors are attracted to suspicious splits. In the next section, we use confidential trading data to directly assess this interpretation.

4. Are small retail investors attracted to suspicious splits?

In this section, we examine confidential account trading data from the SSE to directly identify the buyers of the splitting stocks and consider whether they are less financially sophisticated.

4.1. Retail investor purchases of suspicious splits

We analyze the complete trading account data from the Shanghai Stock Exchange around all stock transfer events from January 1999 through December 2015. This sample includes 39% of the overall stock split sample considered in the preceding analysis. We test the hypothesis that small retail investors are the buyers of suspicious splits because they are known to be attracted to stock splits (e.g., Baker and Gallagher, 1980) and are likely to be relatively uninformed.[26]

We begin by plotting abnormal volume around split announcements from trading day −20 to +60, where t=0 is the announcement date. This window represents approximately one month before until three months after the announcement. Abnormal volume is defined as the daily volume (RMB) divided by the average daily volume (RMB) over the past year. Panel A of Figure. 3 shows that abnormal trading volume is elevated for both types of stocks before the announcement

[26] Circumstantial evidence supports this view as split announcers subsequently experience increases in volatility, volume, and smaller lot sizes, which are price dynamics frequently associated with the trading activity of retail investors (e.g., Schultz, 2000). However, the evidence is merely suggestive because these studies infer trading from trade size and lack trading account records

(approximately +20% on day −5 and +60% on day −1), which suggests that the market is anticipating split activity. In comparison, the abnormal trading volume for forthcoming earnings announcements with no splits is much smaller (approximately 7% and 10% on days −5 and −1, respectively). For both suspicious and nonsuspicious splits, abnormal volume spikes on the announcement date and remains elevated over the next 60 trading days. In contrast, trading volume gradually reverts to normal levels for earnings announcements with no splits. Overall, the total trading volume of suspicious and nonsuspicious splits appears quite similar, but underlying these similarities could be differences in who is buying and selling shares.

To examine these trading dynamics, we plot the cumulative daily net buying around split announcements among the four investor groups. Daily net buying is the total buy minus sells scaled by the average daily volume over the past year (See Section 2.1). We plot the cumulative net buying by small retail investors (accounts < =$5 million RMB), large accounts (accounts > $5 million RMB), institutional investors, and other investors in panel B, C, D, and E, respectively. We separately analyze small and large accounts because investors with large accounts in China are perceived to be more sophisticated and have been shown to exploit small retail investors (Chen, Gao, He, Jiang, and Xiong, 2019). Table 4 provides formal statistical tests of the resulting patterns in the pre- and post-announcement periods.

Panel B of Figure. 3 shows that small retail investors increase their net buying of suspicious splits (solid line) even *before* the split announcement. This pattern is unique to suspicious splits because small retail investors do not significantly accumulate shares in nonsuspicious splits in the pre-announcement period (dotted line). The first column in Table 4 reports that in the preannouncement period, small retail investors are stronger net buyers of suspicious splits (84% of daily average volume, t=3.09) compared to nonsuspicious splits (17% of daily average volume,

t=1.79). The difference is statistically significant ([A]−[B]=67%, t=2.34). The more aggressive net buying of suspicious splits during the pre-announcement period could reflect information leakage on the part of firms announcing suspicious splits. For example, the 2018 CSRC investigation on manipulation activity mentions that manipulators can conspire with management to leak rumors of a split or release false news before the split announcement to attract attention to their shares (See Appendix B). We examine this possible explanation in Section 6.

Upon the split announcement, the plot shows that small retail accounts sharply accelerate their net buying and continue to accumulate shares over the next 60 days for both suspicious and nonsuspicious splits. Column 2 in Table 4 reports that small retail net buying from day 0 to +60 totals 445% (t=3.72) and 264% (t=4.72) of daily average volume, respectively, for suspicious and nonsuspicious splits. The next two rows separate nonsuspicious splits into announcements by regular and SOE firms. Splitting the sample of nonsuspicious splits reveals that retail investors are more attracted to split announcements by regular firms (424% of daily average volume) compared to SOE firms (219% of daily average volume). We observe that small retail investors are unable to distinguish between split announcements by suspicious and nonsuspicious regular firms, as there is no statistical difference in net buying activity between the two types ([A]−[C]=0.21, t=0.20).

Large accounts, shown in panel C of Figure. 3, exhibit strikingly different trading patterns compared to small retail investors. They are net buyers before the announcement of all splits, suspicious and nonsuspicious. This pattern is consistent with the view that large investors are able to anticipate split announcements unconditionally. After the announcement, large investors more aggressively sell holdings over the next 60 days of suspicious splits compared to nonsuspicious splits ([A]−[B] =−59%, t=−1.98). This pattern of accumulating shares before the announcement and unwinding positions afterwards is consistent with a strategy of front-running positive feedback traders, who will subsequently purchase shares in reaction to positive news (De Long, Shleifer, Summers, and Waldmann,1990; Pearson, Yang, and Zhang, 2021).

The level of the selling of suspicious splits by large investors in the post-announcement period is much higher than the accumulated net buying before the split announcement (−85% versus 19%). Since the level of short selling during our sample period is extremely low, and it is at times banned, there are two possible explanations for this result. First, these large investors were already holding positions in these shares. Second, they can acquire shares through private placements or off-exchange block sales and then sell these shares through their accounts. In the next section, we analyze the possibility that suspicious splits are associated with off-exchange block sales.

Institutional investors, shown in Panel D of Figure. 3, are net sellers. They are willing to provide liquidity for both regular and suspicious splits. The negative net buying suggests that they are selling inventory they already held or possibly selling shares obtained through private placement or off-exchange block sales. Panel E shows the net buying for other investors; however, the final two columns of Table 4 show that their net buying is not statistically different from zero for suspicious and nonsuspicious splits in both the pre- and postannouncement periods.

Overall, the trading analysis suggests that small retail investors are the net buyers of these suspicious splits as more sophisticated investors, large accounts and institutional investors, exit their positions.

4.2. Are less sophisticated retail investors more likely to purchase suspicious splits?

Our evidence thus far indicates that suspicious splits attract small retail investors. Compared to large retail investors, this group appears to be relatively less informed. To further study whether suspicious split buyers are less financially sophisticated, we analyze the account characteristics of a random sample of over 120,000 individual accounts during the period from January 2013 to June 2015. We verify that the account size distribution of the random sample is similar to that of the overall sample.

We examine the types of accounts that were more likely to buy suspicious splits by estimating a Poisson regression using Eq. (1).

$$Y_i = \alpha + \beta_1 \times Wealth_i + \beta_2 \times Return\ performance_i + \beta_3 \times Experience_i + \gamma \times \theta_i + e_{i,} \quad (1)$$

where *i* represents an individual account and the dependent variable Y_i is the number of purchase orders of suspicious splits by the account holder over the trading window day=−20 to +60 around the suspicious split announcement. We proxy for investor sophistication using the natural logarithm of the average monthly account size in RMB (*wealth*), average monthly percentage return (*return performance*), and the months since account opening (*experience*) because studies show that financial sophistication is associated with financial wealth, better financial outcomes, and more financial experience (Calvet, Campbell, and Sodini, 2007, 2009; van Rooij, Lusardi, and Alessie, 2011). The calculation of *return performance* excludes all holdings of suspicious splits to ensure that it is not affected by the performance of the split. θ_i represents a vector of control variables that include the age of the account holder, whether the account holder is female, the average monthly number of stocks held in the portfolio, and the average monthly number of purchases. The number of purchases controls for the frequency of trading because high turnover accounts could incidentally buy suspicious splits.

Table 5 reports the results. The evidence indicates that buyers of suspicious splits tend to be less sophisticated. Column 1 shows that investors with smaller accounts, worse return performance, and less experience were more likely to purchase a suspicious split. Accounts that made more overall purchases were also more likely to buy suspicious splits.[27] We find that younger investors and male investors were more likely to purchase a suspicious split. These findings suggest that suspicious split buyers are likely to be overconfident because they trade more frequently and are more likely to be male (Barber and Odean, 2000, 2001).

Although we control for purchase frequency, the results could still reflect the tendency of less sophisticated investors to buy splits, unconditionally. To address this alternative interpretation, we re-estimate the analysis using a subsample of accounts that purchased at least one split during the period of analysis. Column 2 reports the results. We continue to find that less sophisticated investors are more likely to purchase suspicious splits.

We perform additional tests to ensure that our findings are robust. First, we reestimate Eq. (1) using a negative binomial regression. Next, we estimate a standard logit regression where the dependent variable is a dummy equal to one if the account purchases any of the suspicious splits during the sample period, and zero otherwise. Our inferences are unchanged using these alternative econometric models. As a measure of the propensity of buying a suspicious split relative to any split, we calculate the ratio of suspicious split purchases to total split purchases. Using this ratio as the dependent variable, we estimate Eq. (1) using an ordinary least squares regression and a generalized linear model with a logit link, which accounts for the fact that the ratio is bounded by zero and one. Our main inferences are unchanged in the analysis using the suspicious split ratio and are available in the Internet Appendix.

Overall, our analysis of confidential SSE account data demonstrates that less sophisticated retail investors are strongly attracted to suspicious splits. Moreover, they are likely to be overconfident based on their high portfolio turnover and the greater likelihood of being male.

[27] The results are similar using the total number of transactions, which includes buys and sells.

5. How are insiders able to benefit from manipulative splits?

The results in the previous sections suggest that at least some splits are used to manipulate stock prices. To explore the potential beneficiaries of these manipulative splits, we analyze two forms of off-exchange transactions: block trades and share pledge loans. Block trades are typically initiated by insiders or larger shareholders selling their shares, and share pledge loans are loans obtained by executives or large shareholders who pledge their shares as collateral. Both types of transaction have become popular in recent years. The investigation of the Zexi Investment Company scandal revealed that executives conspired with Xiang Xu, the hedge fund manager, to unload blocks and announce splits among other activities to manipulate their share price. The 2018 CSRC investigation of manipulation activities found that manipulators often use share pledge loans to obtain additional funds to acquire their own shares (see Appendix B). We speculate that these off-exchange transactions have become popular in recent years to circumvent detection by stock exchange regulators who heavily scrutinize on-exchange trades by corporate insider and large shareholders.

5.1. Block trades after the announcement of suspicious splits

Block trades are off-exchange transactions with amounts greater than $2 million RMB or 300,000 shares. The counterparties negotiate the trades, typically after trading hours, and report the transaction to the stock exchange. Block trades are a popular method for shareholders with significant holdings to sell a substantial number of shares to institutional investors because regulators restrict shareholders who hold more than 5% of the company's share from selling more than 1% of a company's share within a three-month period on the secondary market. Block trades also avoid the regulatory scrutiny of secondary market transactions. For example, shareholders with significant holdings are required to report their intent to trade at least 15 trading days in advance if they plan to sell on the secondary market.[28] In our sample, block trades tend to transact at a 5% to 6% discount relative to the trading day's closing price, suggesting that they are seller initiated.[29]

Our hypothesis is that insiders use suspicious splits to help off-load blocks at more favorable prices. To explore this possibility, we estimate a monthly panel regression using Eq. (2).

$$Y_{i,t} = \alpha + \beta_1 \times suspicious\ split_{i,(t,\,t-1)} + \beta_2 \times\ split_{i,(t,\,t-1)} + \gamma \times \theta_{i,t-1} + e_{i,t} \qquad (2)$$

$Y_{i,t}$ is the monthly value of block transactions as a percentage of market capitalization. *Suspicious split* is an indicator variable that equals to one if the firm announces a suspicious split in the current or prior month, and zero otherwise. *Split* is an indicator variable that equals to one if the firm announces a split in the current or prior month, and zero otherwise. The indicator includes the current month and prior month because insiders can sell blocks in the immediate period around the split announcement date. θ is a vector of control variables that includes the following measures. Because block sales are affected by firm characteristics and recent trading performance, the control variables include firm size, SOE status, return on assets, the book-to-market ratio, past three-month stock return, past three-month trading turnover, and the three-day return around the most recent earnings announcement. We proxy for financial constraints using investment, leverage, age, and dividend payout. The regressions include year-month fixed effects to capture macro-economic trends and industry-year fixed effects to capture industry trends. We estimate robust standard errors that are clustered by industry-year.

[28] Shanghai Stock Exchange Regulatory Note, 2018. On block trades by executives and key shareholders. Available at: www.sse.com.cn/lawandrules/regulations/csrcannoun/c/4033057.pdf

[29] Since there is a discount, we believe that these trades are initiated by sellers. The discounts in our sample are comparable to the 6% discount from an earlier sample (2003−2009) reported in Bian, Wang, and Zhang (2012).

Table 6 reports the results. In column 1, we observe a significantly positive β_1 estimate and a positive but insignificant β_2 estimate. This result indicates that block trades tend to occur shortly after suspicious split announcements, but not after split announcements, unconditionally. We also observe a significant relation between lock-up expirations and block trades, which suggests that insiders and large shareholders often use block sales to unload their newly unlocked shares. Hence, the β_1 estimate implies that a suspicious split announcement significantly increases the likelihood of a block trade beyond a lock-up expiration. The finding is consistent with the hypothesis that some large shareholders take advantage of the market overreaction to suspicious splits to sell off their shares at favorable prices

To draw stronger inferences about the motives behind suspicious splits, we decompose the suspicious split into its three components and reestimate the regression. We expect that insiders will have a strong desire to announce a split if they have plans to unload their impending unlocked shares using subsequent block sales. Column 2 reports a significantly positive loading on suspicious splits by firms with insiders with lock-up expirations, which indicates a strong link between the split announcement, insider lock-up expiration, and off-exchange block sale. The results support the view that insiders take advantage of the higher postsplit share price to unload shares after their lock-up expiration. Moreover, we observe a significant relation between the announcement of suspicious splits that have atypical timing and block trades. As argued earlier, splits announced outside of regularly scheduled earnings announcements or after poor recent stock performance should raise red flags. This finding is consistent with the idea that managers can announce splits at unconventional times to help off-load blocks.

5.2. *Share pledge loans after the announcement of suspicious splits*

Share pledge loans are loans made to executives or large shareholders who pledge their shares as collateral. These loans were controversial because the proceeds were intended for real investment, but their use was not monitored.[30] Insiders who plan to obtain leveraged loans have strong incentives to artificially boost their share prices to prop up the collateral value.

To investigate whether suspicious splits were used to help obtain these loans, we estimate a monthly panel regression using Eq. (3), where Y_i is the initiation of a share pledge loan as a percentage of market capitalization. Share pledge loans represent a form of shadow banking because non-SOEs have limited access to credit in the Chinese banking system. Cheng, Liu, and Sun (2020) find that share pledge loans tend to cluster in capital-intensive industries, in which financial constraints are more likely to bind. Therefore, we control for firm-level measures of financial constraints and include industry-year fixed effects to absorb industry-level shocks that can affect the ease of raising capital.

The results in column 3 show that the shareholders of suspicious split announcers initiate significantly larger share pledge loans after the split announcement. The coefficient estimate on the split indicator is statistically insignificant, which suggests that there is no effect of splits on future share pledge loans when the splits are not suspicious. We have argued that investors should be suspicious of split announcements that coincide with high accruals because managers who inflate earnings and concurrently use stock splits to attract retail attention could have ulterior motives to prop up their share price. To examine the possibility that such managers are seeking

[30] It was widely rumored that the funds were used for personal speculative investments. In 2018, the SSE restricted the use of proceeds to real corporate investments and explicitly forbade stock market investment (Shanghai Stock Exchange Regulatory Note, 2018. On block trades by executives and key shareholders. Available at: www.sse.com.cn/lawandrules/regulations/csrcannoun/c/4033057.pdf) These loans were lucrative for the lenders. The lenders were typically brokerages, but the ultimate source of capital was often traditional banks (Zhu, 2018).

stock pledge loans, column 4 reports results using the separate components that we used to identify suspicious splits. We find a significant relation between splits identified as suspicious with high accruals and future stock loans. This result is consistent with the view that managers who use splits to inflate their stock price to obtain stock pledge loans also tend to inflate their earnings.

Overall, the results demonstrate how managers might benefit financially from manipulative splits. Notably, these transactions occur off-exchange and are therefore less likely to be detected by stock exchange regulators.

6. Further evidence on manipulation activities

We have stressed that a stock split is one of many choices that can be made to artificially inflate a firm's stock price. But an alternative view is that investors simply misvalue splits (Birru and Wang, 2016). While this interpretation is difficult to rule out, news articles report anecdotes and anonymous tips that document the use of stock splits to facilitate the selling of shares by insiders (see Appendix C).

To provide evidence on another potential manipulation channel, we collect a sample of postings starting in January 2010 and ending in March 2013 on the Guba Eastmoney stock forum following the methodology used in Chang, Hong, Tiedens, Wang, and Zhao (2015). Our message board sample contains 789,461 unique postings on 1,410 stocks, which represents approximately 75% of all stocks listed on the Shanghai and Shenzhen exchanges during this period. Overall, the regression analysis contains 1,156,626 observations, which include all calendar days for stocks covered by the Guba message board during the sample period. Our primary measure of message board activity is the number of characters in the title of the post *(# of title characters)* for each stock on each day. We also collect the number of characters in the main body of the post *(# of post characters*) and the number of posts (*# of posts*) as additional measures of message board activity.

We create an indicator variable called *suspicious split pre-period,* which is equal to one if a suspicious split announcement will occur in the next 14 days, and zero otherwise. Because the outcome is a count variable, we estimate a Poisson regression, following Eq. (3).

$$Message\ board\ activity_{i,t} = \alpha + \beta_1 \times Suspicious\ split\ pre\text{-}period_{i,t} + \eta \times \theta_{i,t-1} + \chi_i + e_{i,t} \qquad (3)$$

Our aim is to test the hypothesis that message board activity is abnormally high in the days leading up to suspicious split announcements. β_1 is an estimate of the effect of a forthcoming suspicious split announcement on message board activity. χ_i represents firm fixed effects, which absorb unobserved firm heterogeneity. Therefore, identification comes from the time variation in message board activity within the same firm. θ_i represents a vector of variables to control for the stock's recent trading performance, which include the logarithm of market capitalization, the monthly stock return in each of the past three months, and the stock turnover in each of the last three months. We calculate *t*-statistics using robust standard errors that are clustered by date.

Table 7 reports the results. In column 1, the significantly positive β_1 estimate indicates an increase in message board activity in the days immediately before a suspicious split announcement. The estimated incidence rate ratio implies that message board activity increases by 1.91 times (t=4.20) on the days immediately preceding a suspicious split announcement relative to days with no forthcoming suspicious splits. Column 2 shows that the effects are similar (β_1=2.06, t=5.36) with the inclusion of firm control variables.

Next, we augment the specification with two indicator variables. *Nonsuspicious preperiod* is an indicator equal to one if a nonsuspicious split announcement will occur in the next 14 days. *Earnings preperiod* is an indicator equal to one if an earnings announcement will occur in the next 14 days. It is important to control for upcoming earnings announcements because most splits are announced concurrently with earnings. The results in column 3 show that the β_1 estimate remains positive and statistically significant (β_1= 1.72, t= 3.05) with the inclusion of these indicators. We also estimate a specification (unreported) to compare the incidence rate ratios of suspicious and nonsuspicious and find that the ratio (1.72÷1.26) is statistically significant at the 5% level. Columns 4 and 5 show that the results are similar using the daily *# of post characters* and daily *# of posts* to measure message board activity.

Overall, the results are consistent with the view that split rumors and/or leakage occur on the Guba message board and lend further credence to the manipulation story.

7. Robustness tests and additional discussions

This section provides additional tests to ensure that our results are robust and are not confounded by the suspicious characteristics or other concurrent corporate announcements (e.g., earning news, cash dividend announcements). We address the possibility that the inverse U-shaped abnormal return patterns surrounding suspicious splits are due to the underlying suspicious characteristics rather than a combination of the split and the suspicious characteristics. Because the majority of split announcements are concurrent with annual earnings releases and dividend announcements, we also need to separate the effect of splits on investor attention from investor reactions to earnings surprises and cash dividend announcements.

We address these concerns by designing two tests that use a matching sample approach. First, we adjust the returns of suspicious split announcers using an alternative benchmark by matching to a sample of nonsplit firms that share common suspicious firm characteristics or concurrently announce corporate actions. Second, we obtain the full SSE trading records from 2013 to 2015, which contains *all* stocks, including nonsplit announcers, to create a trade-based test that allows for a comparison of the trading behavior of retail investors in stocks that are split announcers with their trading behavior in stocks that announced similar earning news, but do not concurrently split their shares.

7.1. Addressing confounding events around suspicious split announcements

To address the possibility that our baseline size-adjusted return benchmark does not adequately control for confounding events, we create alternative return benchmarks using the following matched sample procedure. We match each suspicious split to a sample of stocks in the same quintile of market capitalization in month $t-1$ that did not announce a split and either 1) shared a similar suspicious split characteristic, 2) reported a three-day buy-and-hold market reaction to an earnings announcement in the same quintile as the suspicious split, or 3) announced a dividend in the same month. We calculate the matched sample BHAR by subtracting the suspicious split return from the average return of these matched firms in the period surrounding the suspicious split announcement.[31]

7.1.1. Matching on size and suspicious characteristic

To assess whether the inverse U-shaped abnormal return patterns surrounding suspicious splits reflect the suspicious characteristics rather than a combination of the split and the suspicious characteristics, we match each suspicious split announcement with a sample of stocks in the same quintile of market capitalization in month $t-1$ that did not announce a split but exhibited a similar suspicious characteristic. If a suspicious split exhibits multiple suspicious characteristics, we include matched firms from each characteristic in the matched sample portfolio. We report the BHAR as the difference between the buy-and-hold return of split announcers and the return of the equal-weighted matched sample portfolio.

[31] In performing the matched sample procedure, inevitably, some splits will drop from the sample due to the lack of a corresponding matched firm. To ensure that there are a sufficient number of matched firms, we require that the match sample contains at least five stocks.

Consistent with our main baseline results, panel A of Table 8 reports an inverse U-shaped abnormal return pattern. There is an initial positive market reaction to the split announcement, followed by a positive drift and eventual return reversal from month +4 to +18 (−13.13%, t=−3.40). When we perform this analysis for each type of suspicious split, we find that the excess return using the size/accrual benchmark is much more negative over the entire year and half period (−15.61, t=−2.87). In other words, the returns of stocks with a combination of unfavorable accruals and a split are significantly more negative than those with unfavorable accruals without splits over this sample period.

7.1.2. Matching on size and earnings surprise

Panel B of Table 8 reports the size/earnings surprise matched sample abnormal returns around suspicious split announcements. Consistent with our main analysis, we observe an inverse U-shaped abnormal return pattern around the suspicious split announcement. After the initial positive abnormal return in the month of the announcement (2.74%, t=3.41), suspicious splits experience a positive drift over the next three months and a large return reversal from month +4 to +18 (−14.10%, t=−2.95). This reversal is more negative than the baseline size-adjusted BHAR in Table 3. Moreover, the size/earnings benchmark produces more negative excess return (−8.99%, t=−1.89) over the entire year and a half period compared to the size-adjusted benchmark (−5.09%, t=−1.26). We also observe similar excess return patterns for each individual suspicious split type in the next three rows. These findings suggest that the return patterns associated with suspicious split announcements are not directly caused by concurrent earnings surprises.

Matching firms that announce suspicious splits to firms with similar earnings surprises suggest that our findings are distinct from the postearnings announcement drift (PEAD) phenomenon (e.g., Hirshleifer, Lim, and Teoh, 2009). Moreover, as we show in the Internet

Appendix, the PEAD phenomenon is economically small during our sample period in China.[32] Notably, the PEAD portfolio strategy is driven by the short leg because stocks with positive earnings surprises do not exhibit significantly positive returns in the postannouncement period. Since most split announcers tend to experience strong positive market reactions on earnings announcements, the PEAD phenomenon is unlikely to explain our findings.

Overall, the alternative BHAR using the size/earnings surprise matched sample benchmark suggests that investors react to the suspicious split announcement rather than the earnings surprise. Consistent with the use of splits for stock price manipulation, we continue to observe an inverse U-shaped abnormal return pattern upon the announcement of a suspicious split, consistent with our baseline results.

7.1.3. Matching on size and dividend announcements

Concurrent announcements of cash dividends can also confound our findings if retail investors are attracted to dividends rather than splits. We address this possibility by matching each suspicious split announcement with a sample of stocks in the same quintile of market capitalization in month $t-1$ that did not announce a split but announced a dividend in the same month. We create an equal-weighted portfolio of the matched sample of nonsplit dividend announcers and report the excess return as the difference between the buy-and-hold return of split announcers and this matched sample portfolio.

Panel C of Table 8 continues to show a similar inverse U-shaped abnormal return pattern around the suspicious split announcements based on the size/dividend announcement matched sample. We observe initial positive drift in the three months after the split announcement (1.85%, t=1.74), followed by a significant return reversal from month +4 to +18 (−9.09%, t=−2.50). We

[32] For comparison, the PEAD phenomenon is about four times larger in the U.S. market (Hirshleifer, Lim, and Teoh, 2009).

also calculate the market reactions to cash dividend announcements. In stark contrast to split announcements, dividend announcements do not result in market reactions that are significantly different from zero, which indicates that the periodic announcements of dividends are not surprising to the market on average.[33] These results are available in the Internet Appendix.

Overall, the evidence is consistent with the view that investors react to the suspicious split announcement rather than the dividend announcement.

7.2. Comparison of net buying activity of suspicious splits versus nonsplit stocks

We provide sharper evidence that splits are special in attracting investor attention using the complete trading records of all accounts on the SSE from 2013 to 2015 for all stocks, including nonsplit announcers. We calculate the cumulative daily net buying starting from day −1 to +120 around suspicious split announcements (where day=0 is the announcement date) and compare it to a matched sample of nonsplit stocks in the same quintile of market capitalization in month $t-1$ and three-day buy-and-hold market reaction to earnings announcements in the same quarter.

Consistent with the evidence in Section 4, panel A of Table 9 shows that suspicious splits are considerably more likely to attract the attention of small retail investors. The net buying during the period is 545% (t=2.97) of daily average volume for suspicious splits compared to −27% (t=−0.42) for the matched sample of nonsplit firms that release similar earnings news. The difference is statistically significant (572%, t=2.75). In contrast, column 2 shows that while large accounts are also net buyers of stock splits (1.46, t=2.21), they do not appear to be attracted to the split announcement per se, because they are similarly net buyers of stocks in the matched sample

[33] The issuance of cash dividends is common in the China market (Fang, Hu, and Wang, 2015). Table 1 shows that on average approximately 64% of firms issue a cash dividend each year. We also examine the announcement effect of dividend increases because Michaely, Thaler, and Womack (1995) find that dividend increase announcements in the United States are associated with a positive initial market reaction. However, the initial market returns are actually significantly negative for dividend increase announcements. These results are available in the Internet Appendix.

(1.76, t=6.34; difference=−0.30, t=−0.60). Column 3 reports that institutional investors are the main sellers of shares both around suspicious split announcements (−7.20, t=−3.31) and nonsplit earnings announcements (−1.73, t=−5.17). Other investors (qualified foreign investors and social security accounts), reported in column 4, are much smaller traders in the market.

For comparison, we perform a similar analysis for dividend announcements that did not coincide with a split announcement. Specifically, we match each dividend announcement to a group of nondividend stocks in the same quintiles of market capitalization in month $t-1$ and three-day buy-and-hold market reaction to earnings announcement in the same quarter. Then, we calculate the cumulative daily net buying from day −1 to +120 of the dividend and earnings announcement, where day=0 is the announcement date.

In contrast to the strong net buying of suspicious split announcements, panel B of Table 9 shows that retail investors are net sellers of dividend announcers. Column 1 reports that, in the period surrounding the announcement, retail investors are more likely to sell shares (−0.80, t=−1.87) in dividend announcers compared to the matched sample of non-dividend announcers (−0.54, t=−1.19; difference=−0.26, t=−2.24) in dividend announcers. Column 2 shows that large investors are net buyers of dividend announcers (1.59, t=6.79), but are not more likely to accumulate shares in these stocks compared to the matched sample of non-dividend announcers (1.65, t=6.05; difference=−0.05, t=−0.72). Institutional investors are net sellers of both dividend announcers and the matched sample of non-dividend stocks. Compared to net trading activity of stocks with suspicious splits, the overall net trading activity of dividend announcers is smaller in magnitude, suggesting that dividend announcements attract much less attention than suspicious split announcements.

Overall, the evidence is consistent with the view that splits are special in attracting the attention of retail investors. Dividend announcers do not exhibit the return reversal patterns we observe among suspicious split announcers (See Section 7.1.3) and the trading data reveals that retail investors are not attracted to these stocks.

7.3. Have suspicious splits decreased as the market matured?

We were expecting the manipulative splits to decline over time as the Chinese market matures. However, suspicious splits have actually increased in recent years; while less than 8% of all splits are classified as suspicious in 2003, by the end of our sample in 2015, nearly 40% of the splits are classified as suspicious. Moreover, as we report in the Internet Appendix, the inverse U-shaped abnormal return pattern surrounding suspicious splits is as strong in the latter half of our sample period as in the first half.

We conjecture that the increase in suspicious splits could be due to the emergence of what are known as "market capitalization" consultants, who helped companies comply with regulatory standards and public markets after the 2005−2007 split-share reform[34]. These consultants have recently recommended strategies, which include stock splits, to temporarily boost stock prices. The 2018 CSRC investigation reveals that the consultants suggested several manipulation tactics that also include false rumors on social media platforms (see Appendix B and Section 6).

7.4. Additional robustness tests

We perform additional robustness tests to ensure that our findings are not sensitive to our methodological choices. First, we recalculate the abnormal returns surrounding suspicious split announcements that use an alternative risk benchmark based on market capitalization and the EP

[34] China Securities Regulatory Commission (CSRC), 2005. The administrative methods to implement the split share structure reform. Available at http://www.gov.cn/gzdt/2005-09/05/content_29177.htm.

ratio, following Liu, Stambaugh, and Yuan (2019). Consistent with our baseline findings, the abnormal returns of suspicious splits using this alternative methodology exhibit a similar inverse U-shaped abnormal return in the postannouncement period. Second, we show that our inferences are not sensitive to the specific construct of suspicious splits in our main tests. As a robustness test, we define lock-up expirations of restricted shares that occur in the three (six) months before and after the split announcement as suspicious. We also define suspicious splits with atypical timing as those stocks that are in the bottom 15% or 25% of the past three months' returns and use an alternative measure of accruals as the change in working capital minus depreciation (Sloan, 1996; Liu, Stambaugh, and Yuan, 2019) and categorize high accruals as those firms in the top quintile. These alternative constructs of suspicious splits produce results similar to our main findings. We report the results of these robustness tests in the Internet Appendix.

8. Conclusion

We provide evidence that a salient corporate action, the stock split, has been used to manipulate share prices for the benefit of corporate insiders. We identify a group of stock splits using ex ante information that should raise suspicion given the unusual circumstances surrounding the split announcement. We show that suspicious splits are associated with positive excess returns in the months surrounding their announcements and predictable negative excess returns in the months that follow. Our analysis of trading data reveals that small retail accounts are the net buyers around these suspicious announcements and institutional investors tend to be selling. Further analysis of a subset of our data reveals that, in addition to having small accounts, the buyers of suspicious splits experience poor return performance, tend to trade more, and are more likely to be male.

We also find circumstantial evidence that insiders use splits to boost their share price prior to selling shares in off-exchange block transactions or to obtain loans using company stock as collateral. We also observe significant increases in message board activity on the Eastmoney Guba internet stock forum in the two weeks before the announcement of a suspicious split, which provides evidence that the splits are part of a broader "pump and dump" effort.

We initially conjectured that the recent increase in the number of institutional investors might have led to a decrease in manipulation activities. Our evidence suggests that this has not been the case, perhaps reflecting a possible decline in the general level of retail investor sophistication. Moreover, after the market crash in the latter half of 2015, short selling constraints increased, which could have had the unintended consequence of increasing the prevalence of the type of manipulation that we study in this paper.

Before concluding, it should be stressed that, although the evidence in the paper is inconsistent with our standard notion of efficient markets, given the restrictions on short selling in the Chinese market, one cannot easily arbitrage this form of mispricing.[35] However, the evidence suggests that investors can outperform the market by avoiding stocks that announce suspicious splits and, perhaps, do even better with a strategy of "riding the bubble" (as described in Abreu and Brunnermeier, 2003), which entails initially buying stocks following their suspicious splits, and then selling them prior to the ultimate decline. Indeed, the Chinese business press has described such a stock split trading strategy as a game of "hot potato," suggesting that retail investors could understand the potential for manipulation (see Appendix C), but be overconfident about their ability to time their entrances and exits.

[35] We have had casual conversations with individuals working at Chinese hedge funds who sell futures to offset their long positions. They argue that, because of the short-sale restrictions on individual stocks, selling pressure on the futures tends to make them underpriced, making it difficult to form arbitrage portfolios that avoid the overpriced stocks and hedge using the futures.

References

Abreu, D., Brunnermeier, M.K., 2003. Bubbles and crashes. Econometrica 71, 173−204.

Aggarwal, R. K., Wu, G., 2006. Stock market manipulation. Journal of Business 79, 1915−1953.

Allen, F., Gale, D., 1992. Stock-price manipulation. Review of Financial Studies 5, 503−529.

Allen, F., Haas, M., Nowak, E., Tengulov, A., 2019. Market efficiency and limits to arbitrage: Evidence from the Volkswagen short squeeze. Unpublished working paper. Swiss Finance Institute.

Allen, F., Litov, L., Mei, J., 2006. Large investors, price manipulation, and limits to arbitrage: An anatomy of market corners. Review of Finance 10, 645−693.

Almazan, A., Banerji, S., de Motta, A., 2008. Attracting attention: Cheap managerial talk and costly market monitoring. Journal of Finance 63, 1399−1436.

Baker, H. K., Gallagher, P. L., 1980. Management's view of stock splits. Financial Management 9, 79−77.

Barber, B., Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance 55, 773−806.

Barber, B., Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. Quarterly Journal of Economics 116, 261−292.

Benabou, R., Laroque, G., 1992. Using privileged information to manipulate markets: Insiders, gurus, and credibility. Quarterly Journal of Economics 105, 921−958.

Bian, J., Da, Z., Lou, D., Zhou, H., 2017. Leverage network and market contagion. Unpublished working paper. PBCSF-NIFR.

Bian, J., He, Z., Shue, K., Zhou, H., 2017. Leverage-inducted fire sales and stock market crashes.Unpublished working paper. PBCSF-NIFR.

Bian, J., Wang, J., Zhang, G., 2012. Chinese block transactions and the market reaction. China Economic Review 23, 181−189.

Birru, J., Wang, B., 2016. Nominal price illusion. Journal of Financial Economics 119, 578−598.

Calvet, L., Campbell, J., Sodini, P., 2007. Down or out: Assessing the welfare costs of household investment mistakes. Journal of Political Economy 115, 707−747.

Calvet, L., Campbell, J., Sodini, P., 2009. Measuring the financial sophistication of households. American Economic Review 99, 393−398.

Cao, X., Lemmon, M., Pan, X., Qian, M., Tian, G., 2019. Political promotion, CEO incentives, and the relationship between pay and performance. Management Science 65, 2947−2965.

Carhart, M., Kaniel, R., Musto, D., Reed, A., 2002. Leaning for the tape: Evidence of gaming behavior in equity mutual funds. Journal of Finance 57, 661−693.

Carpenter, J.N., Lu, F., Whitelaw, R.F., 2021. The real value of China's stock market. Journal of Financial Economics 139, 679−696.

Chan, K., Li, F., Lin, T-C., 2019. Earnings management and post-split drift. Journal of Banking and Finance 101, 136−146.

Chang, Y-C., Hong, H., Tiedens, L., Wang, N., Zhao, B., 2015. Does diversity lead to diverse opinions? Evidence from languages and stock markets. Unpublished working paper. Rock Center for Corporate Governance at Stanford University.

Chen, T., Gao, Z., He, J., Jiang, W., Xiong, W., 2019. Daily price limits and destructive market behavior. Journal of Econometrics 208, 249−264.

Chen, Z., Guan, Y., Ke., B., 2013. Are stock option grants to directors of state-controlled Chinese firms listed in Hong Kong genuine compensation? The Accounting Review 88, 1547−1574.

Cheng, Z., Liu, Z., Sun, Y., 2020. Share pledging and financial constraints in China. Accounting & Finance 61(3), 4147−4189.

Comerton-Forde, C., Putniņš, T.J., 2011. Measuring closing price manipulation. Journal of Financial Intermediation 20, 135−158.

Cui, C., Li, F.W., Pang, J., Xie, D., 2019. A behavioral signaling explanation for stock splits: Evidence from China. Unpublished working paper. Singapore Management University.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035−1058.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839−1885.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Positive feedback investment strategies and destabilizing rational speculation. Journal of Finance 45, 379-395.

Devos, E., Elliott, W.B., Warr, R.S., 2015. CEO opportunism? Option grants and stock trades around stock splits. Journal of Accounting and Economics 60, 18−35.

Fan J. P. H., Wong T. J., Zhang T.Y., 2007. Politically connected CEOs, corporate governance, and post-IPO performance of China's newly partially privatized firms. Journal of Financial Economics 84, 330−357.

Fang, C., Hu, X., Wang, J., 2015. Dividends and market reactions in China. Unpublished working paper. Shanghai Jiao Tong University.

Gan, L., Yin, Z., Tan, J., 2015. China household finance survey report 2014. Chengdu: Southwestern University of Finance and Economics (SWUFE).

Golez, B., Jackwerth, J.C., 2012. Pinning the S&P 500 futures. Journal of Financial Economics 106, 566−585.

Grinblatt, M. S., Masulis, R. W., Titman, S., 1984. The valuation effects of stock splits and stock dividends. Journal of Financial Economics 13, 461−490.

Guo, S., Liu, M.H., Song, W., 2008. Stock splits as a manipulation tool: Evidence from mergers and acquisitions. Financial Management 37, 695−712.

Hansman, C., Hong, H., Jiang, W., Liu, J., Meng, J-J., 2018. Riding the credit boom. Unpublished working paper. National Bureau of Economic Research.

He, X., Li., M., Shi. J., Twite. G. J., 2016. Why do firms pay stock dividends: Is it just a stock split? Australian Journal of Management 4, 508−537.

Hirshleifer, D., Jian, M., Zhang, H., 2018. Superstition and financial decision making. Management Science 64, 235−252.

Hirshleifer, D., Lim, S. S., Teoh, S. H., 2009. Driven to distraction: Extraneous events and underreaction to earnings news. Journal of Finance 64, 2289−2325.

Hong, H., Jiang, W., Wang, N., Zhao, B., 2014. Trading for status. Review of Financial Studies 27, 3171−3212.

Hu, G.X., Chen, C., Shao, Y., Wang, J., 2019. Fama-French in China: Size and value factors in the Chinese stock market. International Review of Finance 19, 3−44.

Ikenberry, D. L., Ramnath, S., 2002. Underreaction to self-selected news events: The case of stock splits. Review of Financial Studies 15, 489−526.

Jarrow, R. A., 1992. Market manipulation, bubbles, corners and short-squeezes. Journal of Financial and Quantitative Analysis 27, 311−336.

Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. Journal of Finance 63, 273−310.

Khanna, T., Sunder, S., 1999. A tale of two exchanges. Harvard Business School Case Study.

Khwaja, A.I., Mian, A., 2005. Unchecked intermediaries: Price manipulation in an emerging stock market. Journal of Financial Economics 78, 203−241.

Kumar, A., Lee, C.M., 2006. Retail investor sentiment and return comovements. Journal of Finance 61, 2451−2486.

Lee, C.M., Shleifer, A., Thaler, R.H., 1991. Investor sentiment and the closed-end fund puzzle. Journal of Finance 46, 75−109.

Li, Z., Liu, L., Wei, K. C. J., 2019. Digesting anomalies with the Q-factor model in the China A-share market, Unpublished working paper.

Liu, L. X., Shu, H., Wei, K. C. J., 2017. The impacts of political uncertainty on asset prices: Evidence from the Bo scandal in China. Journal of Financial Economics 125, 286−310.

Liu, J., Stambaugh, R. F., Yuan, Y., 2019. Size and value in China. Journal of Financial Economics 134, 48−69.

Louis, H., Robinson, D., 2005. Do managers credibly use accruals to signal private information? Evidence from the pricing of discretionary accruals around stock splits. Journal of Accounting and Economics 39, 361−380.

Mei, J., Scheinkman, J. A., Xiong, W., 2009. Speculative trading and stock prices: Evidence from Chinese A-B share premia. Annals of Economics and Finance 10, 225−255.

Michaely, R., Thaler, R. H., Womack, K. L., 1995. Price reaction to dividend initiations and omissions: Overreaction or drift? Journal of Finance 50, 573−608.

Nguyen, V., Tran, A., Zeckhauser, R., 2017. Stock splits to profit insider trading: Lessons from an emerging market. Journal of International Money and Finance 74, 69−87.

Ni, S., Pearson, N., Poteshman, A., 2005. Stock price clustering on option expiration dates. Journal of Financial Economics 78, 49−87.

Pearson, N. D., Yang, Z., Zhang, Q., 2021. The Chinese warrants bubble: Evidence from brokerage account records. Review of Financial Studies 34, 264−312.

Peng, W. Q., Wei, K. C. J., Yang, Z., 2011. Tunneling or propping: Evidence from connected transactions in China. Journal of Corporate Finance 17, 306−325.

Piotroski, J.D., Wong, T.J., 2012. Institutions and information environment of Chinese listed firms. Capitalizing China. Joseph Fan and Randall Morck, eds. University of Chicago Press.

Putniņš, T.J., 2012. Market manipulation: A survey. Journal of Economic Surveys 26, 952−967.

Schultz, P., 2000. Stock splits, tick size, and sponsorship. Journal of Finance 55, 429−450.

Shanghai Securities Issue 4, 2018. Notice on stock pledge repo transactions, registration, and settlement business. Available at: www.sse.com.cn/lawandrules/sserules/trading/stock/c/c_20180112_4449493.shtml

Shen, S., Ruwitch, J. China's private placement boom on borrowed time. Reuters, February, 17, 2017. Available at: www.reuters.com/article/us-china-stocks-private-placement/chinas-private-placement-boom-on-borrowed-time-idUSKBN15V2YN (Accessed February 2, 2020).

Sloan, R.G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings?. The Accounting Review 71, 289−315.

Spatt, C. 2014. Security market manipulation. Annual Review of Financial Economics 6, 405−418.

Teoh, S., Welch, I., Wong, T., 1998a. Earnings management and the long-run underperformance of initial public equity offerings. Journal of Finance 53, 1935–1974.

Teoh, S., Welch, I., Wong, T., 1998b. Earnings management and the long-run underperformance of seasoned equity offerings. Journal of Financial Economics 50, 63–100.

van Rooij, M., Lusardi, A., Alessie R., 2011. Financial literacy and stock market participation. Journal of Financial Economics 101, 449−472.

Wang, X. Stock splits to push up share price for share lock-up expiration. CNstock.com, July, 2013. Available at: www.cnstock.com/v_company/scp_dsy/tcsy_gszx/201307/2649702.htm (Accessed February 20, 2020).

Wong, T. J., 2014. Corporate governance research on listed firms in China: Institutions, governance, and accountability. Foundations and Trends in Accounting 9, 259−326.

Xiong, W., Yu, J., 2011. The Chinese warrants bubble. American Economic Review 101, 2723−2753.

Zhu, F., 2018. Equity pledge financing and the Chinese stock market, BIS Quarterly Review, December 2018. 13−14.

Appendix A. Variable definitions

Variable	Description
	Firm characteristics
Size	Market capitalization computed as the previous month's closing price times the total A shares outstanding in millions of RMB. Source: CSMAR
Price	Closing price in RMB at the end of the prior month. Source: CSMAR
Analyst	Number of analysts following the firm. Source: CSMAR
Turnover	Share turnover in the prior quarter calculated as total shares traded divided by tradable shares. Source: CSMAR
Turnover (m−t)	Share turnover in month −t calculated as total shares traded divided by tradable shares. Source: CSMAR
Beta	Beta calculated from the market model of daily returns over the past year. Source: CSMAR
Idiosyncratic volatility	Annualized daily idiosyncratic volatility over the past year. Source: CSMAR
CAR (3-day)	Three-day abnormal buy-and-hold return around earnings announcement defined as the raw return minus the matched size-decile return. Source: CSMAR
Dividend payment	Dummy variable equal to one if the firm pays a cash dividend during the year. Source: CSMAR
Dividend amount	Dummy variable equal to one if the firm pays a cash dividend during the year. Source: CSMAR
Ret (m−t)	Stock return in month −t. Source: CSMAR
Ret (m−3, m−1)	Cumulative stock return from month −3 to month −1. Source: CSMAR
ROA	Return on assets. ROA equals the ratio of a firm's net profit to total assets. Source: CSMAR
Leverage	Total liabilities divided by total assets. Source: CSMAR
BM	Book-to-market ratio defined as the ratio of book equity to market capitalization at December of year t−1. Source: CSMAR
EP	Earnings-to-price ratio defined as the ratio of the change in operating net profit to the market capitalization at the end of the accounting period. Source: CSMAR
Accrual	Operating income minus net cash flows from operations divided by total assets. Source: CSMAR
High accrual	Dummy variable equal to one if the firm reported in the top quintile of accruals, where accruals is defined as net profit minus operation expense, and zero otherwise. Breakpoints are set based on cut-offs from the prior quarter. Source: CSMAR
Lock-up expiration	Dummy variable equal to one if the firm has a lock-up expiration of shares (e.g., private placements, IPOs, SEOs, privatizations) held by influential investors in months –1 to +6. We classify influential shareholders as institutional investors and large shareholders who hold shares with "added restrictions," "added promises," "matched shares," or "extra allotments." The WIND classification codes for these shares are 1, 2, 7, 24−28, 35, 43, 44, 47, 48, 50, and 51. Data begins in 2006/01. Source: WIND
Investment	Total investment divided by total assets. Source: CSMAR
Age	Months since initial exchange listing. Source: CSMAR

SOE	Dummy variable equal to one if the firm is a state-owned enterprise. A state-owned enterprise is a firm whose ultimate owner is the Chinese government. Source: CSMAR
	Split variables
Split	Dummy variable equal to one if the firm announces a split in the current or prior month. Source: CSMAR
Suspicious split	Dummy variable equal to one if a split occurs in the current or prior month and exhibits any of the three types of suspicious splits: 1) lock-up expiration of private placements, 2) atypical announcement timing, or 3) high accruals. Source: CSMAR, WIND
Suspicious split: Lock-up expiration	Dummy variable equal to one if a split occurs in the current or prior month and has lock-up expirations of shares from influential investors (large shareholders and institutional investors) in months –1 to +6. Source: WIND
Suspicious split: Atypical timing	Dummy variable equal to one if a split occurs in the current or prior month and experienced stock returns in the bottom quintile during the previous three months or was announced outside of an earnings announcement. Source: CSMAR
Suspicious split: High accruals	Dummy variable equal to one if a split occurs in the current or prior month and accruals were in the top quintile of accruals, where accruals is defined as net profit minus operation expense. Breakpoints are set based on cut-offs from the prior quarter. Source: CSMAR
	Off-exchange transactions
Block trades	Total monthly value of shares traded through a block trade as a percentage of market capitalization. Block trades have transaction amounts greater than $2 million RMB in value or 300,000 shares. Data begins in 2002/01. Source: CSMAR
Pledge loans	Total monthly value of shares initially pledged as loan collateral as a percentage of market capitalization. Data begins in 2006/01. Source: WIND

Appendix B. China Securities Regulatory Commission (2018): Report on market manipulation cases in the first half of 2018

Available at: http://www.csrc.gov.cn/pub/newsite/jcj/gzdt/201808/t20180813_342582.html
Last accessed 3 September 2021

Excerpt based on author's translation

In the first half of the year, the CSRC investigated 40 market manipulation cases. The investigation of these events during the first half of the year reveals the following manipulation strategies:

1. Corporate insiders made misleading statements and fabricated false information. Some colluded with external institutions under the guise of market value management to release information including issuing stock splits, announcing "pre-increased performance," and deliberately releasing misleading statements to influence investor expectations.
2. The actors illegally gathered large amounts of funds, abused leveraged transactions, used false declarations, made continuous transactions, and employed other methods to manipulate stock prices. This enticed the market to follow suit, resulting in large fluctuations in individual stock prices, creating excessive volatility.
3. The manipulators used social media to issue stock analysis, forecasts, and investment proposals. Before releasing information, manipulators bought shares, then made recommendations, and subsequently sold shares in secret to obtain illegal proceeds. Some illegally used QQ and WeChat groups to recommend stocks to induce other investors to purchase shares.
4. Cross-border manipulation of market cases using interconnection mechanisms still occurs. Following the investigation of Tang Hanbo's use of the Shanghai-Hong Kong Stock Connect mechanism to manipulate the market case in 2016, in the first half of this year, the private equity fund−related employees opened up a stock market in Hong Kong to hoard their chips and implement manipulation in the Mainland to realize profitability of overseas chips.

Appendix C. Examples of business press coverage on stock price manipulation using stock splits in the China market

1. Wang, Xueqing, 2013, Stock splits to push up share price for share lock-up expiration. CNstock.com, Jul. Available at: www.cnstock.com/v_company/scp_dsy/tcsy_gszx/201307/2649702.htm (Last accessed February 20, 2020)

2. *TenCent Financial News*, 2013. The hidden secret of high stock splits: Don't be the last person in pass the parcel's game. 11 Jul. Available at: finance.qq.com/a/20130711/001123.htm (Last accessed February 1, 2016)

3. *Xinmin News*, 2015. The game of stock split in financial market. 27 Mar. Available at: xinmin.news365.com.cn/ljzjrc/201503/t20150327_1792873.html (Last accessed February 1, 2016)

4. Liu, C, Dong, T., 2016. Share splits raise stock market suspicions. Caixin Global, 01 Dec. Available at: www.caixinglobal.com/2016-12-01/share-splits-raise-stock-market-suspicions-101021512.html (Last accessed February 20, 2020)

5. Xiao, L., 2017. Collusion networks increasingly common form of market rigging in China. Caixin Global, 7 Aug. Available at: www.caixinglobal.com/2017-08-07/collusion-networks-increasingly-common-form-of-market-rigging-in-china-101127360.html (Last accessed February 20, 2020)

Figure. 1.

Buy-and-hold abnormal monthly returns of split announcements.

Figure 1 plots the average buy-and-hold abnormal monthly returns for stock splits announced between 1999/01 and 2015/06. The buy-and-hold abnormal return is the buy-and-hold return of the split announcer minus the size-decile return benchmark (DGTW-benchmark for U.S. splits). U.S. splits are all split announcers in the U.S. stock market (dotted-dashed line). Regular splits are split announcers by non-SOEs that are not categorized as suspicious (dotted line). SOE splits are split announcements by SOE firms (dashed line). Suspicious splits are split announcements by non-SOEs that meet one or more of the following criteria: lock-up expirations, atypical timing, or high accruals (solid line).

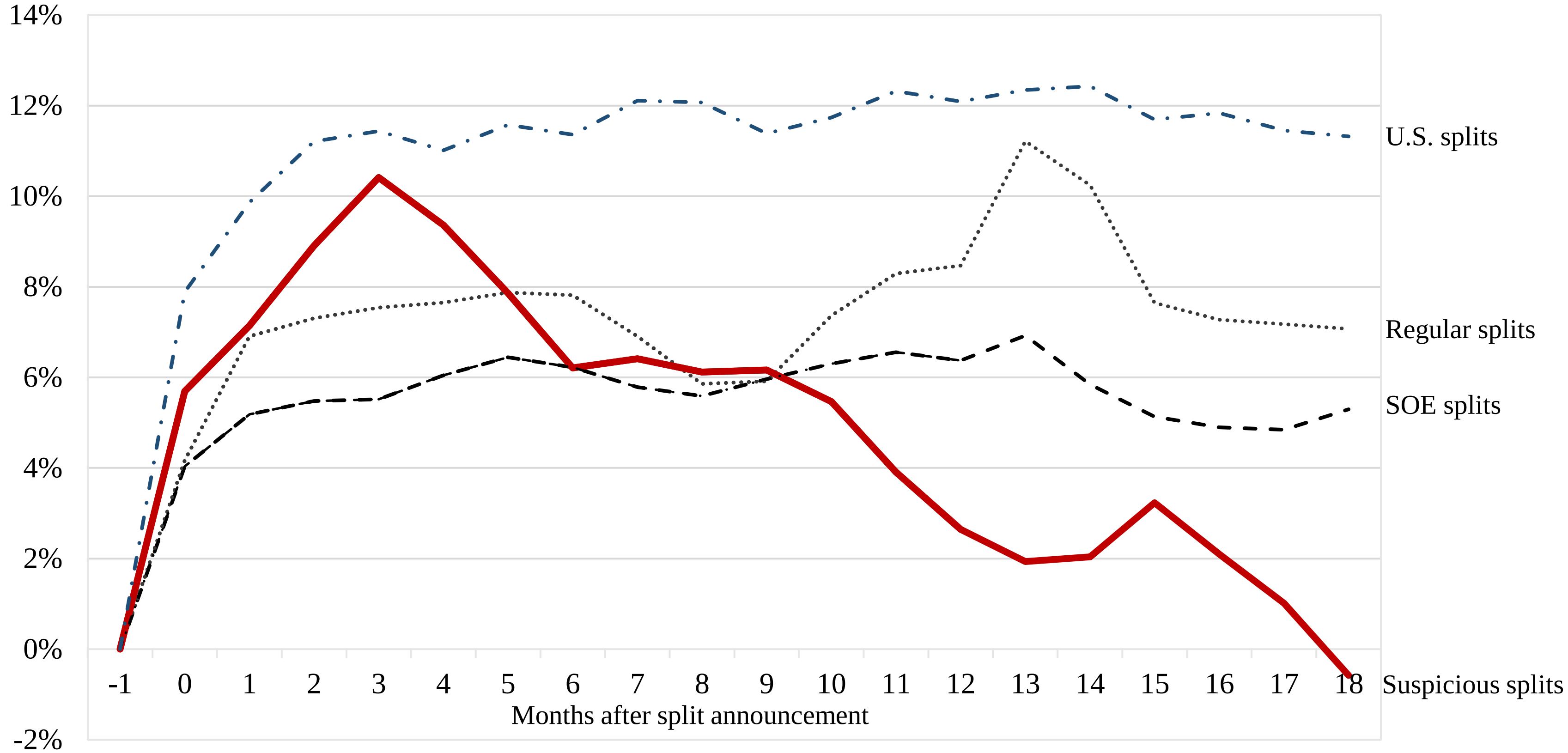


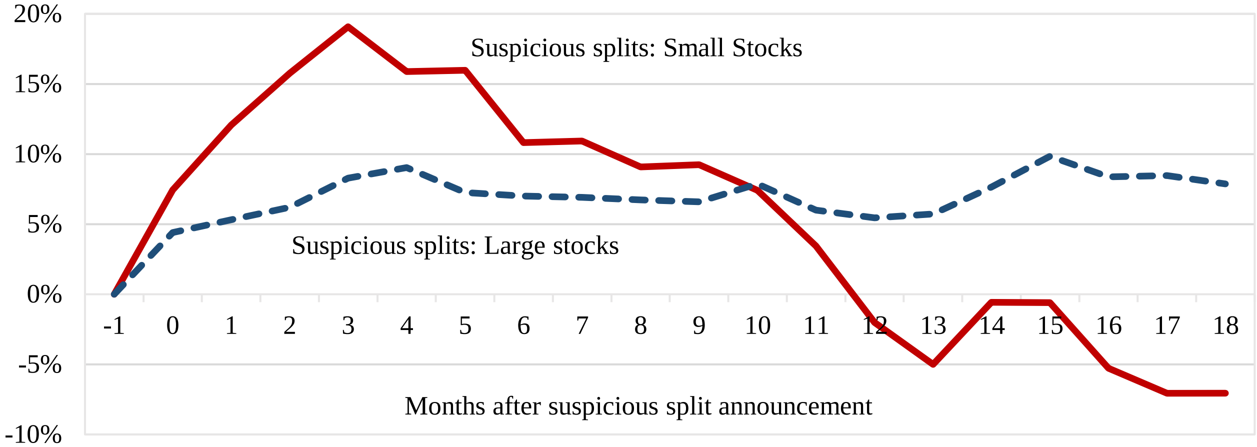
Figure. 2.

The effect of retail attention on returns of suspicious splits.

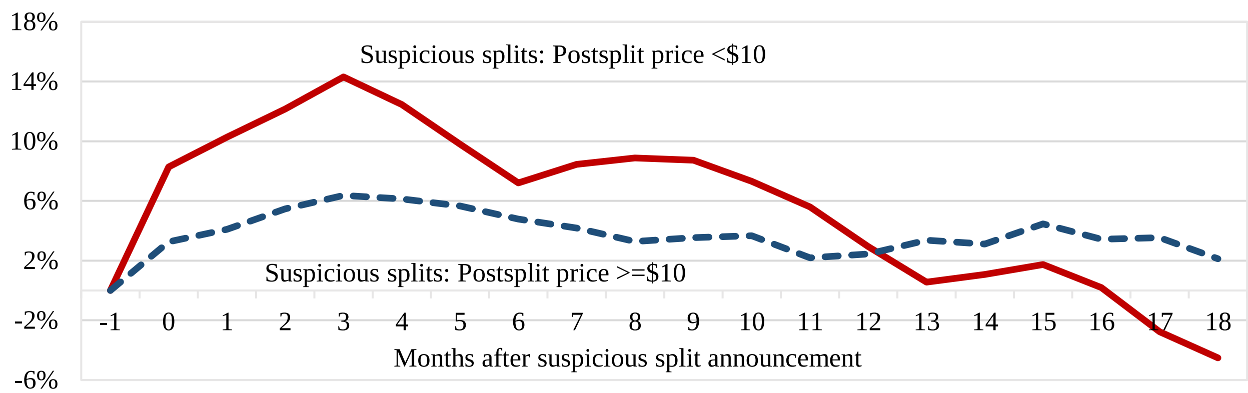
Figure. 2 plots the average monthly buy-and-hold abnormal returns (BHAR) of subsamples of suspicious splits with high and low retail attention. Panel A plots the BHAR of suspicious splits of small (large) stocks formed using the bottom 30 (top 70) percentile of market capitalization ranked on the previous quarter breakpoints. Panel B plots the BHAR of suspicious splits that experience a drop in the postsplit nominal price to less than $10 and those for which the postsplit nominal price remains >=$10. Panel C plots the BHAR of suspicious splits with unlucky listing codes and other listing codes that do not satisfy the unlucky criteria. An unlucky listing code contains the unlucky digit 4 but not any of the lucky digits 6, 8, or 9. Suspicious splits are split announcements by firms that meet one or more of the following criteria: lock-up expirations, atypical timing, or high accruals. The sample period is from 1999/01 to 2015/06.

Figure. 2. Continued

Panel A. Small versus large stocks



Panel B. Postsplit price < $10 versus postsplit price >= $10



Panel C. Unlucky listing codes versus all other listing codes

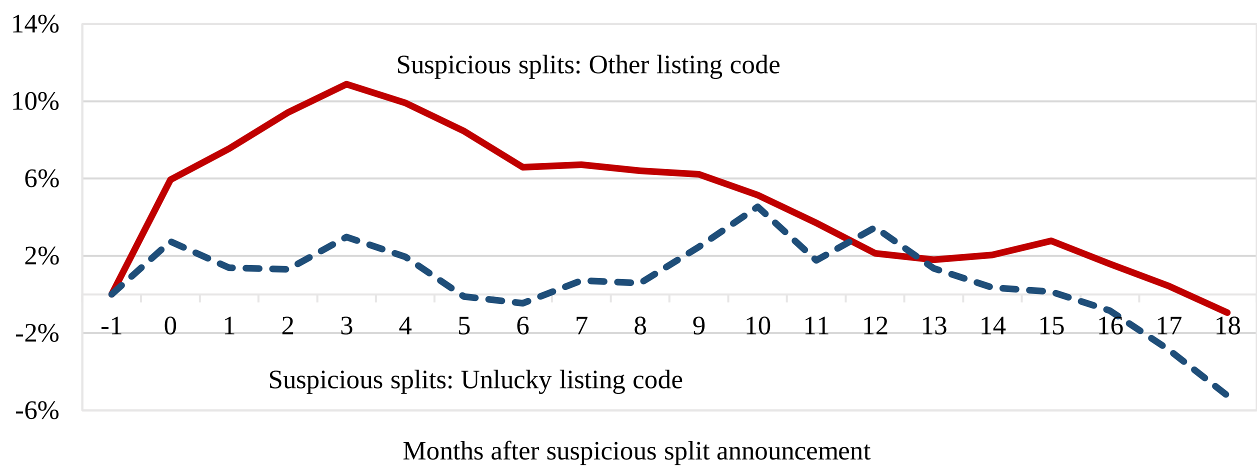
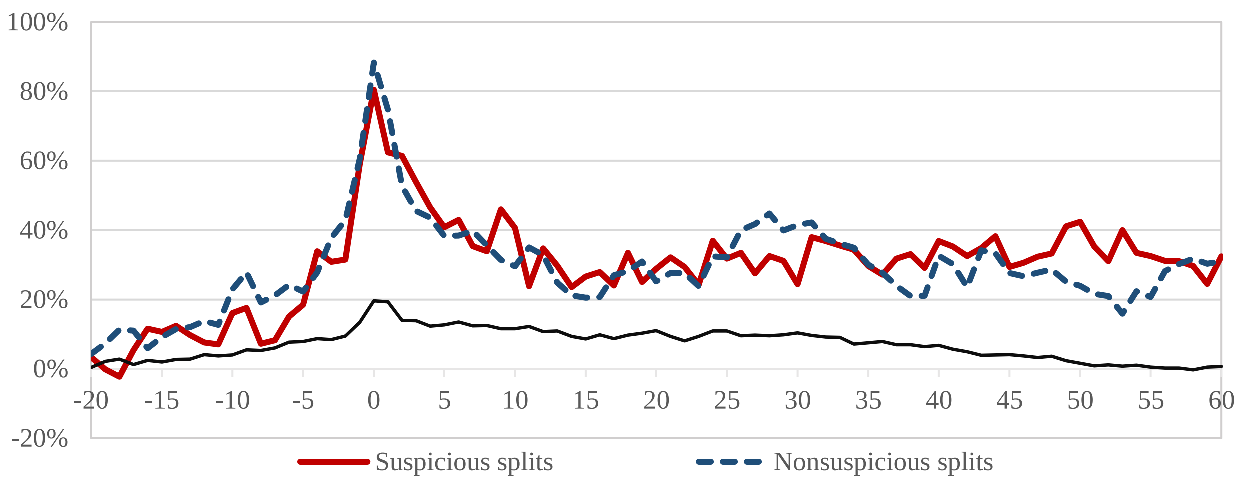


Figure. 3.

Abnormal volume and cumulative daily net buying by investor groups around split announcement.

Figure. 3 plots abnormal volume and the average cumulative daily net buying by investor type around the announcement of a stock split for stocks on the Shanghai Stock Exchange. Panel A plots abnormal volume around the announcement of suspicious splits, nonsuspicious splits, and earnings with no concurrent split. Abnormal volume is defined as the daily dollar volume divided by the average daily dollar volume over the past year. Panels B, C, D, and E plot the cumulative net buying of small retail investors with trading accounts <$5 million RMB, large accounts with accounts >=$5 million RMB, institutional investors, and other investors, respectively. We report average cumulative net buying for suspicious splits (solid red line) and nonsuspicious splits, which consist of both regular + SOE splits (dashed blue line). Net buy is the total buy minus sell volume for each investor group divided by average daily volume over the past year. The sample consists of all stock transfers on the SSE announced between 1999/01 and 2015/06.

Panel A. Abnormal volume around split announcements



Panel B. Small retail investors' cumulative daily net buy around split announcements

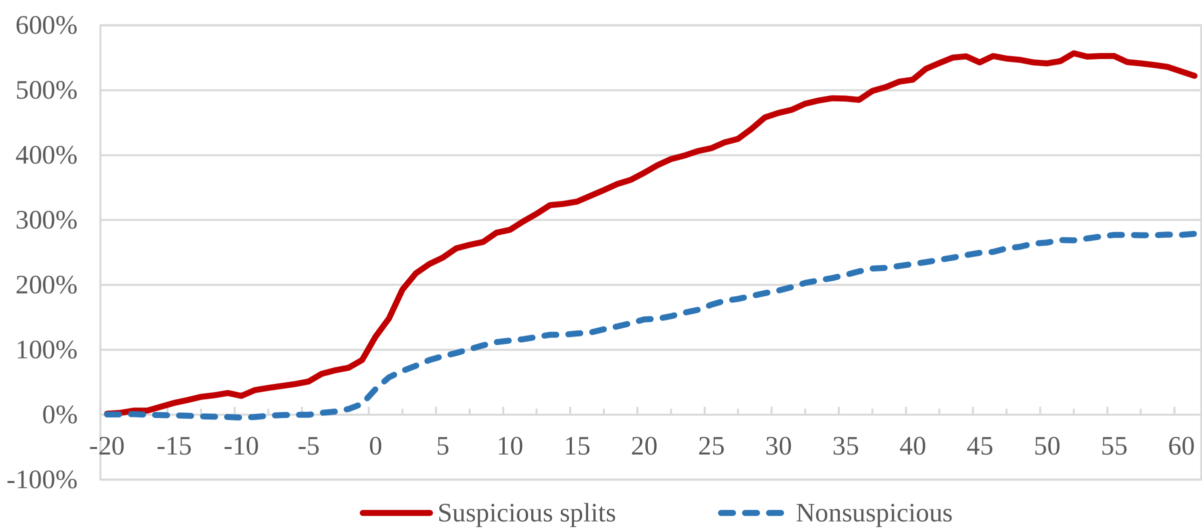
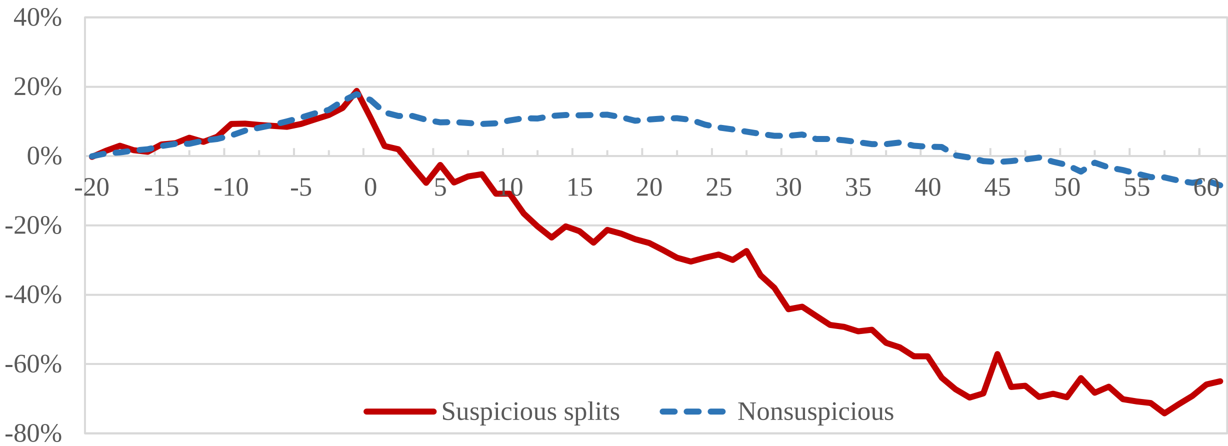
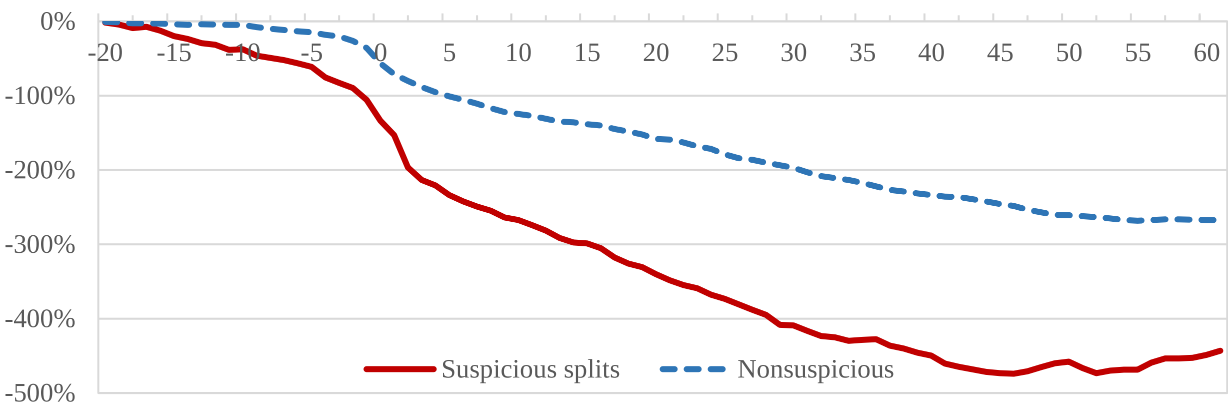


Figure. 3. Continued

Panel C. Large investors' cumulative daily net buy around split announcements



Panel D. Institutional investors' cumulative daily net buy around split announcements



Panel E. Other investors' cumulative daily net buy around split announcements

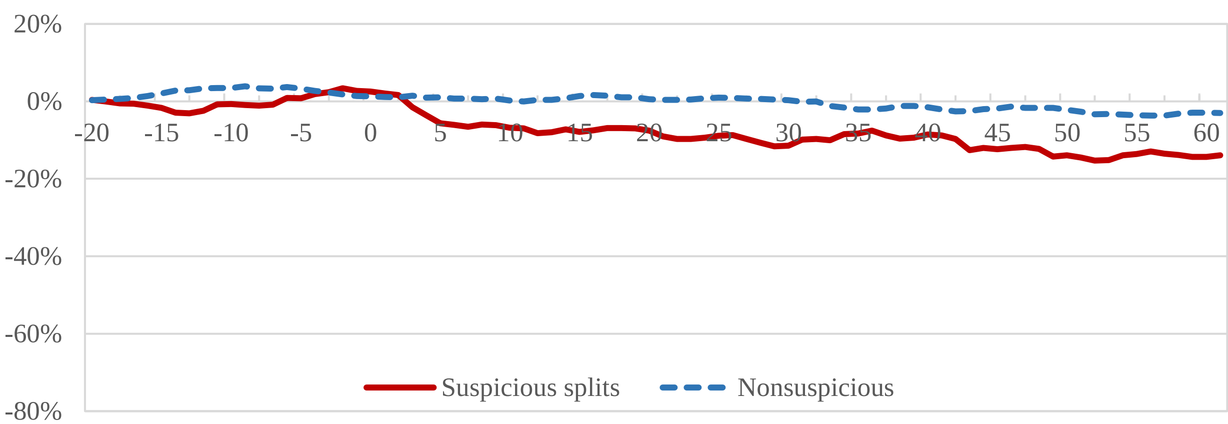


Table 1

Summary statistics of split announcers.

Table 1 reports the summary statistics of stock splits announcers. Panel A reports the time-series monthly average firm characteristics of firms that announce and did not announce stock splits. Panel B reports the time-series average monthly average firm characteristics of suspicious splits and nonsuspicious split announcers. The last two columns of each panel report the average difference and *t*-statistic between the two samples. The bottom row reports the time-series annual average number of unique firms in each respective sample. Appendix A provides variable definitions. The sample period is from 1999/01 to 2015/06.

Panel A. Comparison of split firms and nonsplit firms

	Split firms	Nonsplit Firms	Difference	*t*-stat
Size (in millions RMB)	$6,447	$5,298	$1,149	(5.85)
Price	$17.57	$12.30	5.27	(12.09)
Analyst	10.2	6.3	3.9	(4.22)
Turnover (qtr)	39.9%	42.6%	−2.7%	(−1.84)
Beta	0.95	0.98	−0.03	(−1.40)
Idiosyncratic volatility	33.7%	33.26%	0.44%	(0.86)
CAR (annual EA)	1.76%	−0.33%	2.09%	(18.94)
Dividend payment	63.8%	64.28%	−0.53%	(−2.96)
Ret (m−3, m−1)	15.0%	12.1%	3.0%	(2.12)
ROA	6.3%	2.9%	3.3%	(13.39)
Leverage	43.8%	48.7%	−4.9%	(−13.00)
BM	0.38	0.89	−0.52	(−7.43)
EP	4.2%	5.1%	−0.9%	(−1.98)
Accrual	1.9%	-1.1%	3.0%	(11.90)
SOE	1.9%	-1.1%	3.0%	(11.90)
N (annual average)	219	1,725		

Panel B. Comparison of suspicious splits with nonsuspicious splits

	Suspicious	Nonsuspicious	Difference	*t*-stat
Size (in millions RMB)	$5,491	$6,777	−$1,285	(−2.77)
Price	$18.00	$17.41	0.59	(1.19)
Analyst	10.5	10.3	0.3	(0.47)
Turnover (qtr)	37.6%	39.7%	−2.2%	(−1.11)
Beta	0.92	0.96	−0.04	(−3.43)
Idiosyncratic volatility	32.85%	33.81%	−0.96%	(−1.50)
CAR (annual EA)	2.06%	1.68%	0.38%	(1.58)
Dividend payment	62.96%	64.01%	−1.05%	(−0.33)
Ret (m−3, m−1)	5.7%	16.7%	−11.1%	(−4.34)
ROA	6.6%	6.2%	0.5%	(1.35)
Leverage	41.9%	44.7%	−2.7%	(−1.75)
BM	0.34	0.39	−0.05	(−5.16)
EP	3.8%	4.3%	−0.5%	(−2.69)
Accruals	5.3%	1.2%	4.1%	(5.15)
SOE	0.0%	69.5%	−69.5%	(−19.03)
N (annual average)	46	172		

Table 2

Abnormal returns around split announcement: SOE vs. non-SOE splits.

Table 2 reports the average buy-and-hold abnormal returns around split announcements for all split announcements and SOE/non-SOE split announcers. The average buy-and-hold abnormal return is calculated as the buy-and-hold return minus the size-decile benchmark where t=0 is the calendar month (day) of the split announcement. Panel A (B) reports the monthly (daily) abnormal returns around all stock split announcements. t-statistics (presented in parentheses) are calculated using robust (White) standard errors that are clustered by calendar month. The sample period is from 1999/01 to 2015/06.

Panel A. Monthly abnormal returns around split announcements

	N		[−3 to −1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
All splits	3716	mean	4.75	4.45	2.15	−2.47	4.77
		t-stat	(6.25)	(13.98)	(3.31)	(−1.59)	(3.11)
Non-SOE	1712	mean	3.91	4.87	2.99	−5.31	3.55
		t-stat	(3.71)	(9.74)	(3.53)	(−2.17)	(1.47)
SOE	2004	mean	5.47	4.09	1.43	−0.05	5.81
		t-stat	(7.35)	(11.30)	(1.84)	(−0.03)	(3.45)

Panel B. Daily abnormal returns around split announcements

	N		[−10, −2]	[−1,+1]	[+2,+10]
All splits	3716	mean	2.66	1.85	−0.03
		t-stat	(11.47)	(13.62)	(−0.20)
Non-SOE	1712	mean	2.88	2.04	0.22
		t-stat	(8.34)	(10.17)	(0.87)
SOE	2004	mean	2.47	1.69	−0.25
		t-stat	(11.80)	(10.68)	(−1.04)

Table 3

Suspicious splits: Monthly abnormal returns around split announcement.

Table 3 reports the average monthly buy-and-hold abnormal returns around split announcements for suspicious splits. The average buy-and-hold abnormal return is calculated as the buy-and-hold return minus the size-decile benchmark where month=0 is the calendar month of the split announcement. Panel A presents suspicious splits and regular non-SOE splits. Panel B presents subsamples of suspicious split announcers by type. *Lock-up expiration* is non-SOE split announcers that have lock-up expirations that occur in months −1 to +6 around the split announcement of private placements or restricted shares held by influential shareholders. The sample period for the lock-up analysis is from 2006/01 to 2015/06 because reporting on lock-ups begins in 2006. *Atypical timing* is non-SOE split announcers that were either (1) in the bottom quintile in returns during the previous three months or (2) announced a split outside of an earnings announcement period. *High accrual* is non-SOE split announcers that are in the top quintile of accruals. *t*-statistics (presented in parentheses) are calculated using robust (White) standard errors that are clustered by calendar month. The sample period is from 1999/01 to 2015/06.

Panel A. Suspicious vs. regular splits (Non-SOE firm sample)

	N		[−3 to −1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
Suspicious	787	mean	−2.25	5.69	3.26	−10.99	−0.58
		t-stat	(−1.92)	(6.26)	(2.39)	(−3.40)	(−0.18)
Regular non-SOE	925	mean	9.14	4.17	2.76	−0.47	7.07
		t-stat	(8.05)	(7.77)	(3.77)	(−0.14)	(2.13)

Panel B. Suspicious splits by type

	N		[−3 to −1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
Lock-up expiration	146	mean	0.50	4.71	4.72	−13.63	−2.18
		t-stat	(0.32)	(3.69)	(2.09)	(−2.98)	(−0.49)
Atypical timing	468	mean	−7.85	6.10	3.49	−9.74	1.33
		t-stat	(−4.20)	(5.04)	(1.86)	(−2.51)	(0.33)
High accruals	344	mean	2.56	5.35	2.92	−14.64	−5.09
		t-stat	(1.85)	(4.57)	(2.71)	(−3.54)	(−1.26)

Table 4

Trader net buying activity around suspicious split announcement.

Table 4 reports the average cumulative net buying in the preannouncement (t−20 to −1) and postannouncement (t=0 to +60) period for each investor type for split announcements on the Shanghai Stock Exchange during the period from 1999/01 to 2015/06. Small retail is trading accounts with <$5 million RMB. Large accounts are trading accounts >=$5 million RMB. Institutional investors include mutual funds, hedge funds, and other types of institutional investors. Other investors include qualified foreign investors and social security accounts. Nonsuspicious splits consist of both regular firms and SOE firms that announced splits, but not classified as suspicious. t-statistics (presented in parentheses) are calculated using robust (White) standard errors that are clustered by calendar month.

	Small retail		Large accounts		Institutional investors		Other investors	
	[−20 to −1]	[0 to +60]	[−20 to −1]	[0 to +60]	[−20 to −1]	[0 to +60]	[−20 to −1]	[0 to +60]
[A] Suspicious split	0.84	4.45	0.19	−0.85	−1.06	−3.43	0.03	−0.17
	(3.09)	(3.72)	(1.95)	(−2.74)	(−3.34)	(−3.62)	(0.69)	(−1.47)
[B] Nonsuspicious split	0.17	2.64	0.18	−0.25	−0.36	−2.35	0.01	−0.04
	(1.79)	(4.72)	(7.39)	(−4.87)	(−3.73)	(−4.82)	(0.50)	(−0.62)
Subsample of nonsuspicious								
[C] Non-SOE split	0.20	4.24	0.24	−0.44	−0.48	−3.53	0.04	−0.27
	(1.40)	(4.17)	(5.38)	(−3.29)	(−2.95)	(−3.82)	(0.86)	(−2.01)
[D] SOE split	0.16	2.19	0.16	−0.20	−0.33	−2.01	0.01	0.02
	(1.34)	(4.25)	(6.06)	(−3.92)	(−2.81)	(−4.44)	(0.24)	(0.26)
Difference between suspicious and nonsuspicious splits								
[A]−[B]	0.67	1.81	0.01	−0.59	−0.69	−1.09	0.01	−0.13
Suspicious−nonsuspicious	(2.34)	(1.85)	(0.07)	(−1.98)	(−2.04)	(−1.41)	(0.33)	(−1.23)
[A]−[C]	0.64	0.21	−0.05	−0.41	−0.57	0.10	−0.01	0.10
Suspicious−non-SOE	(2.20)	(0.20)	(−0.47)	(−1.30)	(−1.59)	(0.11)	(−0.25)	(0.69)
[A]−[D]	0.68	2.26	0.02	−0.65	−0.73	−1.42	0.02	−0.19
Suspicious−SOE	(2.26)	(2.15)	(0.24)	(−2.12)	(−2.09)	(−1.71)	(0.55)	(−1.69)

Table 5

Are less sophisticated investors more likely to buy suspicious splits?

Table 5 reports results from a Poisson regression of the number of suspicious splits purchased on retail investor characteristics from the Shanghai Stock Exchange using a random sample of individual accounts during the period from 2013/01 to 2015/06. Column 1 analyzes all the accounts in the random sample. Column 2 analyzes a subsample of accounts that purchased a stock split. *Wealth* is the natural logarithm of the average monthly account value in RMB. *Return performance* is the average monthly return performance calculated by accumulating the daily return of positions held from the prior day excluding all suspicious split holdings. *Experience* is the number of months the account has been open until the beginning of our sample period (Jan 2013). If the starting month is after Jan 2013, we set the value equal to zero. *# of stocks bought* is the average monthly number of stocks bought. *# of stocks held* is the average monthly number of stocks held in the account. *Age* is the age of the account holder at Jan 2013. *Female* is a dummy variable equal to one if the account holder is female, and zero otherwise. *t*-statistics (presented in parentheses) are calculated using robust (White) standard errors.

Sample:	All retail accounts with transactions	Subsample of retail accounts with split purchases
Investor sophistication		
Wealth	−1.871	−1.650
	(−9.31)	(−6.44)
Return performance	−0.137	−0.011
	(−30.95)	(−3.09)
Experience	−0.049	−0.037
	(−14.99)	(−11.02)
Transaction activity		
# of stocks bought	0.042	0.028
	(75.88)	(36.75)
# of stocks held	0.005	0.003
	(3.65)	(1.72)
Demographics		
Age	−0.003	−0.003
	(−3.26)	(−3.37)
Female	−0.124	−0.059
	(−7.42)	(−3.55)
Intercept	−3.655	−1.146
	(−73.73)	(−22.85)
Pseudo R-squared	0.057	0.023
Observations	123,160	35,716

Table 6

Who are the beneficiaries?

Table 6 reports results from a monthly panel regression of block trades (columns 1 and 2) and share pledge loans (columns 3 and 4) initiated as a percentage of market capitalization on the recent announcement of a suspicious split. Block trades is defined as the total monthly value of shares traded through block trade as a percentage of market capitalization. Block trades have transaction amounts greater than $2 million RMB in value or 300,000 shares. Share pledge loans is defined as the total monthly value of shares initially pledged as loan collateral as a percentage of market capitalization. *Suspicious split* is a dummy variable equal to one if the suspicious split is announced in the current or preceding month, and zero otherwise. *Split* is a dummy variable equal to one if the split is announced in the current or preceding month, and zero otherwise. *Lock-up expiration* is a dummy variable equal to one if the split is announced in the current or preceding month and has a lock-up expiration in the month –1 to +6 around the split announcement. *Atypical timing* is a dummy variable equal to one if the split is announced in the current or preceding month and the stock was in the bottom quintile of returns during the previous three months or the split is announced outside of an earnings announcement, and zero otherwise. *High accrual* is a dummy variable equal to one if the split was announced in the current or preceding month and was in the top quintile of accruals, where accruals is defined as net profit minus operation expense. The regressions include year-month fixed effects and industry-year fixed effects. *t*-statistics (presented in parentheses) are calculated using robust standard errors that are clustered by industry-year. Appendix A provides variable definitions. The sample period for block trades is from 2002/01 to 2015/07. The sample period for pledge loans is from 2006/01 to 2015/07.

Table 6 Continued

	(1) Block trades	(2) Block trades	(3) Pledge loans	(4) Pledge loans
Suspicious split	0.89		0.02	
	(2.81)		(2.02)	
Suspicious split: Lock-up expiration		1.19		−0.01
		(2.12)		(−0.61)
Suspicious split: Atypical timing		1.14		0.01
		(2.05)		(0.80)
Suspicious split: High accrual		−0.02		0.03
		(−0.03)		(2.25)
Split	0.09	0.09	0.00	0.00
	(0.92)	(0.91)	(0.61)	(0.83)
Lock-up expiration	2.49	2.49	0.00	0.00
	(4.53)	(4.53)	(1.34)	(1.45)
High accrual	−0.04	−0.04	0.00	0.00
	(−1.22)	(−1.18)	(0.75)	(0.63)
Ret (m−3, m−1)	0.43	0.44	0.00	0.00
	(3.83)	(3.84)	(1.63)	(1.60)
SOE	−0.52	−0.52	−0.03	−0.03
	(−6.65)	(−6.56)	(−4.45)	(−4.45)
log(Size)	−0.13	−0.13	0.01	0.01
	(−5.68)	(−5.69)	(3.89)	(3.89)
ROA	0.01	0.01	−0.00	−0.00
	(0.84)	(0.84)	(−7.27)	(−7.27)
BM	−0.17	−0.17	−0.01	−0.01
	(−3.19)	(−3.19)	(−3.72)	(−3.73)
CAR (3-day)	0.03	0.04	0.01	0.01
	(0.18)	(0.20)	(1.88)	(1.86)
Turnover	−0.05	−0.05	−0.00	−0.00
	(−0.67)	(−0.67)	(−1.78)	(−1.78)
Investment	0.02	0.02	−0.01	−0.01
	(0.25)	(0.23)	(−1.82)	(−1.82)
Leverage	−0.27	−0.27	0.01	0.01
	(−2.33)	(−2.32)	(2.25)	(2.24)
Age	−0.45	−0.45	0.00	0.00
	(−6.06)	(−6.07)	(1.53)	(1.54)
Dividend amount	−1.79	−1.80	−0.26	−0.26
	(−1.64)	(−1.65)	(−3.78)	(−3.76)
Constant	5.12	5.12	−0.08	−0.08
	(8.57)	(8.58)	(−3.04)	(−3.04)
R-squared	0.0330	0.0330	0.023	0.023
Observations	266,269	266,269	209,638	209,638
Sample period	2002/01−2015/07	2002/01−2015/07	2006/01−2015/07	2006/01−2015/07

Table 7

Stock message board activity preceding suspicious split announcements.

Table 7 reports estimates from a Poisson regression of message board activity on the period preceding the announcement of suspicious splits. The posts are from the Eastmoney Guba message board and contains 789,461 total postings and 1,410 stocks. The dependent variables are *# of title characters*, *# of post characters*, and *# of posts*. *Suspicious preperiod* is a dummy that equal to one if a suspicious split announcement will occur in the next 14 days, and zero otherwise. *Nonsuspicious preperiod* is a dummy that equal to one if a nonsuspicious split will occur in the next 14 days, and zero otherwise. *Earnings preperiod* is a dummy that equal to one if an earnings announcement will occur in the next 14 days, and zero otherwise. The regression includes firm fixed effects. *t*-statistics (presented in parentheses) are calculated using robust standard errors that are clustered by date. Appendix A provides variable definitions. The sample period starts in 2010/01 and ends in 2013/03.

	(1) # of title characters	(2) # of title characters	(3) # of title characters	(4) # of post characters	(5) # of posts
Suspicious preperiod	1.91	2.06	1.72	1.68	1.71
	(4.20)	(5.36)	(3.05)	(3.05)	(3.08)
Nonsuspicious preperiod			1.26	1.34	1.24
			(1.30)	(1.64)	(1.20)
Earnings preperiod			1.39	1.39	1.39
			(2.03)	(2.02)	(2.02)
Market cap (*m*-1)		0.12	0.12	0.10	0.12
		(−17.63)	(−17.26)	(−18.21)	(−17.00)
Return (*m*-1)		25.03	25.05	25.86	25.18
		(7.91)	(8.12)	(8.18)	(8.13)
Return (*m*-2)		52.36	48.89	53.97	49.36
		(13.76)	(13.18)	(12.43)	(13.39)
Return (*m*-3)		38.69	36.44	27.86	38.69
		(9.09)	(8.99)	(8.07)	(9.17)
Turnover (*m*-1)		0.71	0.71	0.72	0.70
		(−2.41)	(−2.53)	(−2.58)	(−2.58)
Turnover (*m*-2)		0.57	0.59	0.61	0.58
		(−3.50)	(−3.56)	(−3.44)	(−3.58)
Turnover (*m*-3)		0.94	0.93	0.99	0.91
		(−0.57)	(−0.73)	(−0.16)	(−0.85)
Observations	1,156,626	1,156,626	1,156,626	1,156,626	1,156,626
Pseudo *R*-squared	0.0247	0.115	0.118	0.112	0.120

Table 8

Robustness test: Monthly abnormal returns around suspicious split announcements using alternative return benchmarks.

Table 8 reports the average monthly buy-and-hold abnormal returns around split announcements using a matched sample approach. Panel A matches each suspicious split to a sample of nonsplit stocks in the same quintile of market capitalization in month *t*–1 and with the same suspicious characteristic. Panel B matches each suspicious split to a sample of nonsplit stocks in the same quintile of market capitalization in month *t*–1 and same quintile of earnings surprise defined as the three-day market reaction to earnings announcement in the same month. Panel C matches each suspicious split to a sample of nonsplit stocks in the same quintiles of market capitalization in month *t*–1 and that announced a cash dividend in the same month. Month *t*=0 is the calendar month of the split announcement. *t*-statistics (presented in parentheses) are calculated using robust (White) standard errors that are clustered by calendar month. The sample includes splits announced concurrently with earnings announcements during the period from 1999/01 to 2015/06.

Panel A. Alternative BHAR: Size/suspicious characteristic benchmark

	N		[−3 to −1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
Suspicious*	655	mean	2.60	4.72	1.43	−13.13	−6.14
		t-stat	(3.89)	(5.46)	(1.33)	(−3.40)	(−1.59)
Suspicious types							
Lock-up expiration	146	mean	-1.10	4.62	5.51	−9.37	2.50
		t-stat	(-0.66)	(3.89)	(2.79)	(−1.90)	(0.62)
Atypical timing	303	mean	0.11	4.41	-0.02	−6.23	−1.71
		t-stat	(0.34)	(5.25)	(-0.02)	(−1.52)	(−0.34)
High accruals	322	mean	1.00	5.37	1.77	−23.76	−15.61
		t-stat	(0.72)	(4.01)	(1.25)	(−4.27)	(−2.87)

Panel B. Alternative BHAR: Size/earnings surprise benchmark

	N		[−3 to −1]	[month 0]	[+1 to +3]	[+4 to+18]	[0 to +18]
Suspicious*	554	mean	−5.89	2.74	1.67	-14.10	-8.99
		t-stat	(−5.43)	(3.41)	(1.62)	(-2.95)	(-1.89)
Suspicious types							
Lock-up expiration	109	mean	0.01	3.52	5.24	−19.74	−8.87
		t-stat	(0.00)	(2.58)	(1.72)	(−3.82)	(−1.90)
Atypical timing	256	mean	−18.45	1.62	−0.28	−7.85	−6.56
		t-stat	(−16.97)	(1.50)	(−0.20)	(−1.37)	(−1.08)
High accruals	285	mean	1.00	3.40	2.51	−19.92	−13.12
		t-stat	(0.71)	(3.61)	(2.10)	(−3.84)	(−2.58)

Table 8 Continued

Panel C. Alternative BHAR: Size/cash dividend benchmark

	N		[−3 to −1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
Suspicious*	531	mean	−6.01	4.36	1.85	−9.09	−2.07
		t-stat	(−5.81)	(4.18)	(1.74)	(−2.50)	(−0.60)
Suspicious types							
Lock-up expiration	106	mean	−0.97	5.21	5.67	−15.44	−2.34
		t-stat	(−0.49)	(2.65)	(1.88)	(−2.76)	(−0.55)
Atypical timing	257	mean	−17.84	3.42	0.15	−2.00	1.89
		t-stat	(−16.13)	(2.84)	(0.11)	(−0.45)	(0.41)
High accruals	262	mean	0.72	4.85	2.25	−17.30	−9.34
		t-stat	(0.53)	(3.90)	(1.76)	(−3.71)	(−2.02)

Table 9

Robustness test: Trader net buying activity around suspicious split announcement compared to matched sample.

Table 9 reports the average cumulative total daily net buying in the period around the suspicious split (Panel A) or dividend announcement (Panel B) for each investor type on the Shanghai Stock Exchange during the period from 2013/01 to 2015/06. Panel A matches each suspicious split to a sample of nonsplit stocks (Matched sample) in the same quintile of market capitalization in month *t*–1 and three-day market reaction to earnings announcement in the same quarter. Panel B matches each dividend announcer to a sample of nondividend stocks (Matched sample) that are in the same quintiles of market capitalization in month *t*–1 and three-day market reaction to earnings announcement in the same quarter. Small retail includes trading accounts with <$5 million RMB. Large accounts are trading accounts >=$5 million RMB. Institutional investors include mutual funds, hedge funds, and other types of institutional investors. Other investors include qualified foreign investors and social security accounts. *t*-statistics (presented in parentheses) are calculated using robust (White) standard errors that are clustered by calendar month.

Panel A. Net buying activity of suspicious splits and a matched sample of nonsplit firms with similar size and earnings surprise

	Small retail	Large accounts	Institutional investors	Other
	[−1 to +120]	[−1 to +120]	[−1 to +120]	[−1 to +120]
Suspicious split	5.45	1.46	−7.20	0.29
	(2.97)	(2.21)	(−3.31)	(0.78)
Matched sample	-0.27	1.76	−1.73	0.23
	(-0.42)	(6.34)	(−5.17)	(1.16)
Difference	5.72	−0.30	−5.47	0.06
	(2.75)	(−0.60)	(−2.36)	(0.24)
N	110	110	110	110

Panel B. Net buying activity of dividend announcers and a matched sample of non-dividend firms with similar size and earning surprise

	Small retail	Large accounts	Institutional investors	Other
	[−1 to +120]	[−1 to +120]	[−1 to +120]	[−1 to +120]
Suspicious split	−0.80	1.59	−0.91	0.12
	(−1.87)	(6.79)	(−3.38)	(0.81)
Matched sample	−0.54	1.65	−1.23	0.11
	(−1.19)	(6.05)	(−5.43)	(1.02)
Difference	−0.26	−0.05	0.32	0.01
	(−2.24)	(−0.72)	(3.11)	(0.13)
N	1,650	1,650	1,650	1,650

Internet Appendix

This is the Internet Appendix for "Corporate actions and the manipulation of retail investors in China: An analysis of stock splits." It contains supplementary information, additional tests, and robustness checks discussed in the main text of the paper.

1. Trading volume on the SSE by investor type

Figure 1 provides a summary of the trading volume by investor type on the SSE during the period 2013-2015. Retail accounts account for 89% of average trading (60 % small accounts and 29% large accounts).

2. U.S. splits

We describe additional details of the analysis of the U.S. sample that is referred to in the text. Table 1 reports the average buy-and-hold abnormal return around stock split announcements in the United States from 1999 to 2015. The average BHAR is calculated as the buy-and-hold return minus the DGTW (Daniel, Grinblatt, Titman, and Wermers, 1997) benchmark, where t=0 is the calendar month of the split announcement. The DGTW benchmark is calculated at the beginning of each month by calculating a value-weighted portfolio return of stocks in the same quintile of market capitalization in month $t-1$, book-to-market ratio, and past return ($t-12$ to $t-1$) using dependent sorting. Splits in the U.S. experience excess returns over the initial three-month post-announcement period (2.89%, t=3.73) that does not reverse over the following 15 months.

3. Suspicious splits with atypical timing: Falsification test

We classify stock splits with poor recent stock performance as suspicious because stock splits typically occur after periods of strong stock performance. Hence, the unusual timing of such poor-performing splits should raise flags amongst more vigilant investors. To assess the validity of our assertion, we perform a falsification test by analyzing splits in the non-suspicious sample that experience a high price runup; these split-announcing firms reside in the top quintile of past three-month return. We analyze the non-suspicious split sample to remove the confounding effects of other suspicious characteristics. The idea is that split announcers with strong recent stock performance are less likely to be using splits to manipulate their share price.

Figure 2 reports the results. We observe no difference in the post-announcement abnormal returns for splits with strong stock performance compared to non-suspicious splits that did not experience a high price runups. The result lends additional support to the view that investors should be suspicious of firms that announce splits after poor recent stock performance.

4. Retail sentiment and suspicious splits: Analyst coverage

We perform an additional test to analyze the effect of retail sentiment on suspicious splits by sorting suspicious splits based on analyst coverage. Because analyst coverage is correlated with size, we size-adjust analyst coverage as follows. First, we sort all stocks into deciles based on market capitalization at the previous year-end. Then within each size decile, we sorted stocks into deciles based on analyst coverage. We define low (high) analyst coverage suspicious splits as those in the bottom 30 (top 70) percentile of size-adjusted analyst coverage.

Figure 3 presents the results. We observe more extreme run-up and reversal among stocks with low analyst compared to those with high analyst coverage. The findings lend further credence to the idea that retail attention affects the post-announcement return behavior of suspicious splits.

5. Suspicious splits and investor sophistication: Sample collection and robustness tests

We provide additional information on the sample collection process and describe additional robustness tests. A random sample is taken from the entire population of retail trading accounts during the period January 2013 to June 2015 using the following procedure. First, we keep account numbers ending with 1 and 6, then take a random sample of 1% of these accounts. We require that account information for age and gender are available. The final sample contains a total of 123,160 accounts. We verify that the account size distribution of the random sample is similar to that of the overall sample.

Table 2 reports the results of the robustness tests. Columns 1 and 2 report results from a negative binomial model using equation (1). Columns 3 and 4 report results from a standard logit regression where the dependent variable is a dummy equal to one if the account purchases any of the suspicious splits during the sample period, and zero otherwise. Columns 5 and 6 report results from a generalized linear model (GLM) with a logit link using the ratio of suspicious split purchase to total split purchases as the dependent variable. This ratio captures the propensity to buy a suspicious split relative to any split. Columns 7 and 8 report analysis using OLS. Our main inferences are unchanged across these alternative econometric specifications.

6. Comparison of splits with dividend announcements

In the main text, we discuss the possibility that investors are attracted to dividend announcements, not split announcements. Table 3 reports the market reaction to dividend announcements. We observe that dividend announcements exhibit distinctly different return patterns compared to split announcements. We conclude that the post-announcement return patterns of suspicious splits are not due to concurrent dividend announcements.

7. Lack of post earnings announcement drift in China market

Post-earnings announcement drift (PEAD) is the phenomenon in the United States that stocks with extreme earnings surprise continue to experience significant price drift in the post-announcement period. Therefore, it is possible that the post-split return drift we document in China could be a manifestation of the PEAD phenomenon because split announcements are often concurrent with earnings announcements and generate positive abnormal returns and positive postannouncement drift. To our knowledge, the existence of PEAD in the relatively young China market has not been examined before. Therefore, we explore the returns to a PEAD strategy and assess whether it could explain the split announcement drift we find in the paper.

To create a PEAD strategy, each quarter, we sort stocks into five groups based on three-day abnormal market reaction breakpoints from the prior eight quarters of earnings announcement. Then we calculate the average returns and t-statistics over the next 60 days. We begin this analysis in 2002 because firms in China were required to report quarterly earnings only starting in 2002.

We find that PEAD is unlikely to explain our findings because the PEAD phenomenon is non-existent for positive earnings surprise. Table 4 presents average buy-and-hold returns from t+2 to +60 of stocks sorted in quintiles based on three-day abnormal return around earnings announcement (reported in the bottom row). The results indicate that stocks with the most extreme negative earnings surprise exhibit significant post earnings announcement drift in the 60 days after announcement, with a realized return of −1.12% (t=−4.70). Notably, stocks with the most extreme positive earnings surprise exhibit no post earnings announcement drift (0.05%, t=0.16). Positive-Negative represents the average difference in returns between the Positive and Negative surprise portfolios each quarter.

Since PEAD is a relatively small economic phenomenon in the Chinese markets, it appears an unlikely explanation for the stock split announcement returns patterns. For comparison, the PEAD phenomenon is about four times larger in the U.S. market (Hirshleifer, Lim, and Teoh, 2009). More importantly, firms that announce stock splits tend to have positive earnings surprises, but stocks with positive earnings surprise do not in general experience post-earnings announcement drift. Overall, the evidence suggests that PEAD is an unlikely explanation for the stock split return patterns.

8. Sub-period analysis

Table 5 reports our main baseline BHAR results by sub-period. We reports the average buy-and-hold abnormal returns around split announcements for suspicious split announcements in the early and later half of our sample period.

9. Additional robustness tests

Table 6 reports tests to ensure our findings are robust to our methodological choices. Our main analysis calculates abnormal returns using a size benchmark equal to the value-weighted portfolio of stocks in the same decile of market capitalization at the end of year $t-1$ as the split announcer. We choose a size adjustment as our main benchmark because the shell premium for reverse mergers in China is substantial. Moreover, given the relatively short history of the China market, the debate surrounding the best benchmarking approach is still unsettled. Nevertheless, in this analysis, we show our main findings are unchanged using a size-value benchmark proposed by Liu, Stambaugh, and Yuan (2019). Specifically, they find that size and value, as captured by the earnings to price ratio, because explains returns premiums in the China market.

We construct size/value benchmarks following a similar approach developed in Daniel, Grinblatt, Titman, and Wermers (1997). Each December end, we rank stocks on market capitalization at the end of December. For stocks above the 30% of market capitalization, we split the sample of stocks in half. Then within each half, we further sort stocks based on E/P ratio into terciles. For each size/EP group, we calculate the value-weighted portfolio returns and hold this portfolio construction constant for the following year. For stocks in the bottom 30% of market capitalization, we set the benchmark to the value-weighed size decile at the end of December. Panel A of Table 5 reports similar patterns as our main findings using these benchmarks.

Our definition of suspicious split characteristics is somewhat arbitrary, but as we show in the following analysis, our findings are robust to alternative constructs of suspicious split characteristics. First, we define those lock-up expirations of private placements or restricted shares held by influential shareholders that occurs in the three (six) months before and after the split announcement as suspicious. Second, we also define suspicious splits with atypical timing as those stocks that are ranked in the bottom 15% or 25% of past three month returns. Third, we define an alternative measure of accruals as the change in working capital minus depreciation following the definition in Liu, Stambaugh, and Yuan (2019), and categorize high accruals as those firms in the top quintile. The pattern of results in panel B suggests our findings are robust to these alternative definitions.

10. Xu Xiang and the Zexi Investment Company scandal

On June 7, 2017, Xu Xiang, the manager of Zexi Investment Company, was convicted of insider trading and sentenced to a five- and a half year jail term and fined 11 billion yuan.[1] Xu Xiang purchased off-exchange blocks that were later sold in the secondary market after conspiring with management to release rosy forecasts in an effort to manipulate the share price. The legal ruling reports details from an investigative study of 13 instances where Xu Xiang conspired with management to manipulate their firm's stock price. Eleven of those cases involved the use of stock splits to attract the attention of retail investors. Based on our classification, eight of the 11 splits qualify as suspicious based on our definitions. Although this is a small sample, it suggests that our simple ex ante suspicious characteristics are relatively good at identifying splits that have a manipulation motive.

[1] Yu, X., (2017, January 23) Once China's hedge fund guru, Xu Xiang sentenced to 5.5 years in prison for market manipulation. *South China Morning Post*. https://www.scmp.com/business/money/article/2064582/once-chinas-hedge-fund-guru-xu-xiang-sentenced-55-years-prison-role Accessed 23 August 2021

The court documents from this ruling provide a rare glimpse into a case where additional evidence indicates that insiders were indeed using stock splits with the intention to manipulate their share price. In Exhibit 2, we plot the of the abnormal returns around these 11 split events. We find that the stock price increases substantially in the initial three months following the split and falls dramatically over the next 15 months. This is an exaggerated pattern of the suspicious splits returns in the main analysis.

Figure 1

Trading volume by investor type on the SSE during 2013-2015

This figure reports the fraction of total trading volume by investor types on the SSE from 2013/01 to 2015/12. Small retail are trading accounts with <=$5 million RMB. Large accounts are trading accounts >$5 million RMB. Mutual fund are registered mutual funds. Other institutions include hedge funds and other types of institutional investors. SSQFII include qualified foreign investors and social security accounts.

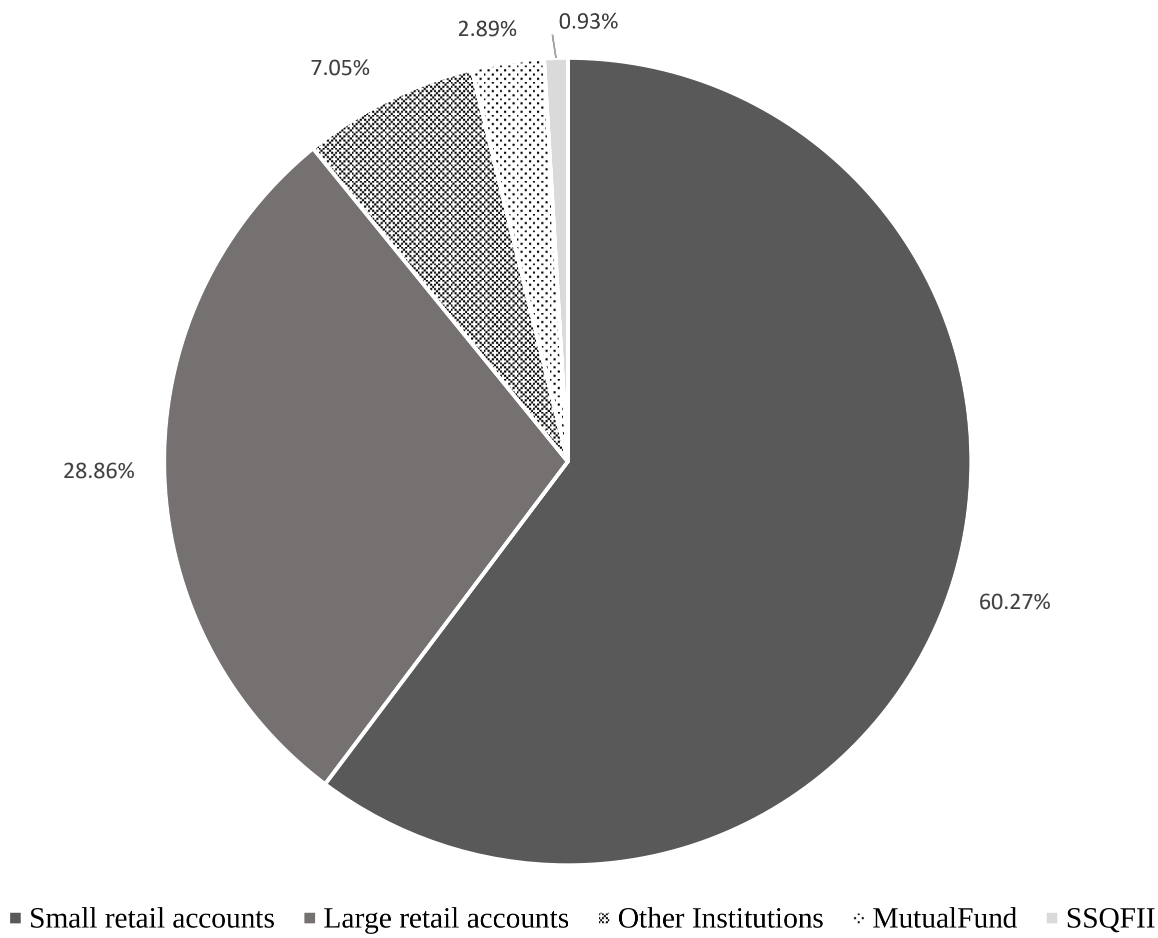


Figure 2

Falsification tests for atypical timing classification of suspicious splits: Buy-and-hold abnormal returns of high past return splits

Figure 2 plots the average buy-and-hold abnormal returns of non-suspicious splits with high past returns compared to those with normal past returns. High price returns are defined as split-announcing firms that reside in the top quintile of past three-month return. Suspicious splits are split announcements by firms that meet one or more of the following criteria: lockup expirations, atypical timing, or high accruals. The sample period is from 1999/01 to 2015/06.

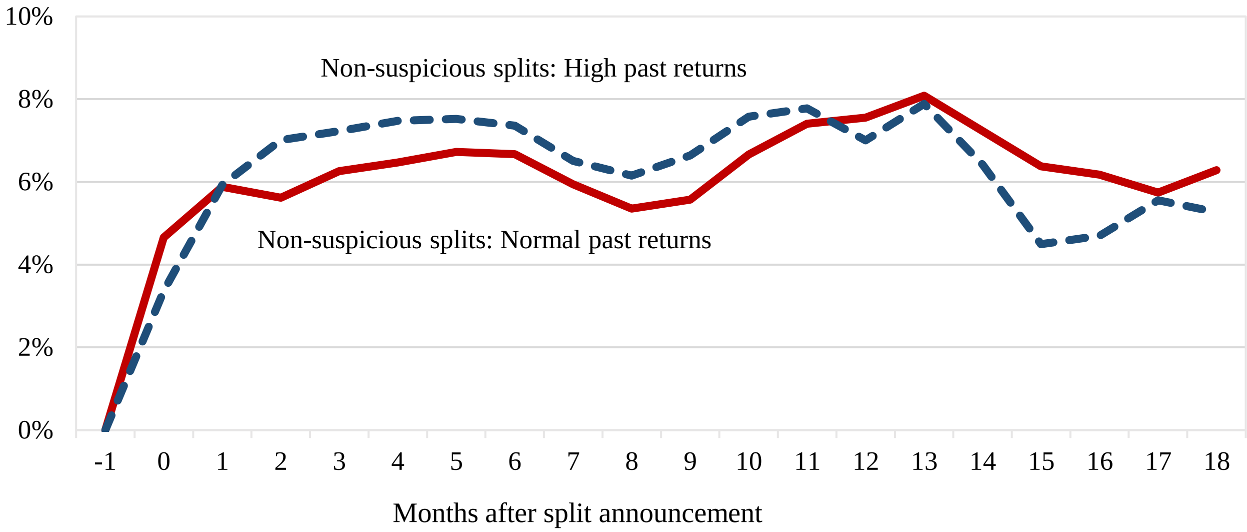
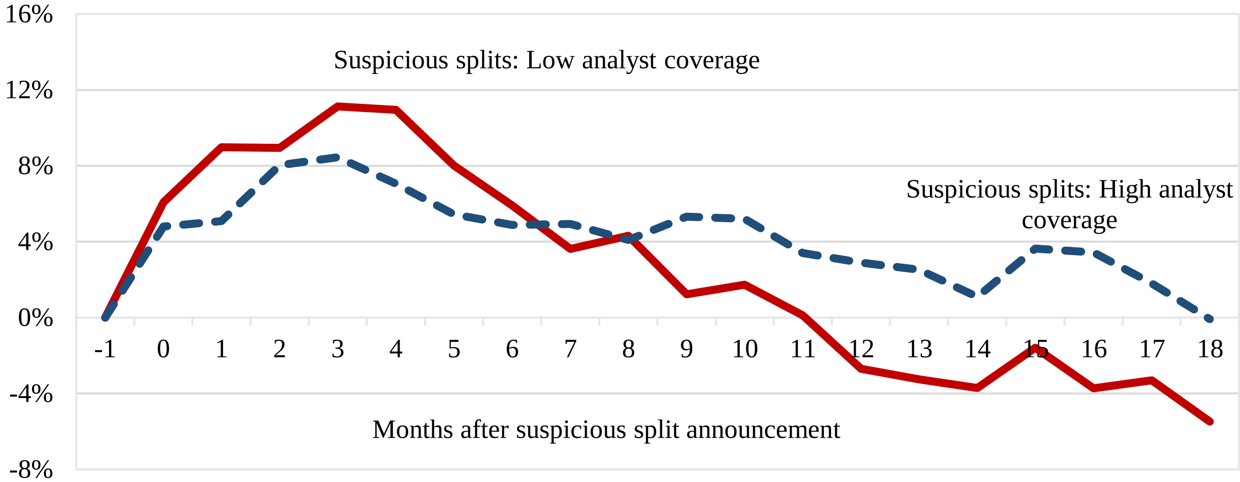


Figure 3

Buy-and-hold abnormal returns of suspicious splits

Figure 3 presents the average buy-and-hold abnormal returns (BHAR) of subsamples of suspicious splits. Panel A plots of the BHAR of low (high) market capitalization suspicious splits formed using the bottom 30 (top 70) percentile of market capitalization based on previous quarter breakpoints. Firms are sorted into deciles based on market capitalization at the previous year-end. Then within each decile, firms are sorted into deciles based on analyst coverage. Panel B plots the BHAR of a subsample of large stock suspicious splits that experience a drop in the post-split nominal price to less than $10 and those where the post-split nominal price remains >=$10. Suspicious splits are split announcements by firms that meet one of the following criteria: lockup expirations, atypical timing, or high accruals. The sample period is from 1999/01 to 2015/06.

Panel A. Low versus high analyst coverage



Panel B. Post-split price < $10 versus post-split price >=$10 for large stocks only

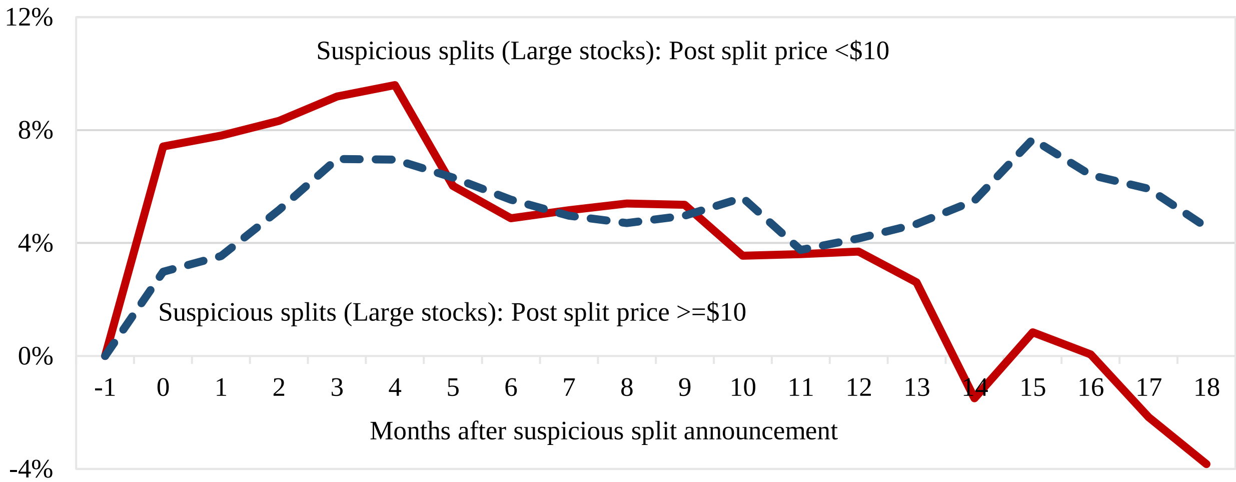


Table 1

Monthly abnormal returns around split announcement for U.S. Market

This table presents average buy-and-hold abnormal returns (BHAR) around split announcements for the United States market from 1999/01 to 2015/06. The BHAR is calculated as the buy-and-hold return minus the DGTW benchmark. *t*-statistics (presented in parenthesis) are calculated using robust (White) standard errors and clustered each calendar month.

	N		[-3 to -1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
United States	2432	mean	19.52	7.88	2.89	0.00	11.43
		t-stat	(7.97)	(10.23)	(3.73)	(0.00)	(8.06)

Table 2

Robustness test for account characteristics

This table reports results from regressions of the number of suspicious splits purchased or the ratio of suspicious splits to total splits purchased on retail investor characteristics from the Shanghai Stock Exchange using a random sample of individual accounts during the period 2013/01 to 2015/06. Column 1 analyzes all the accounts in the random sample. Column 2 analyzes a subsample of accounts 1 that purchased a stock split. *Wealth* is the natural logarithm of the average monthly account value in RMB. *Return performance* is the average monthly return performance calculated by accumulating the daily return of positions held from the prior day excluding all suspicious split holdings. *Experience* is the number of months the account has been open until the beginning of our sample period (Jan 2013). If the starting month is after Jan 2013, we set the value equal to zero. *# of stocks bought* is the average monthly number of stocks bought. *# of stocks held* is the average monthly number of stocks held in the account. *Age* is the age of the account holder at Jan 2013. *Female* is a dummy variable equal to one if the account holder is female, and zero otherwise. *t*-statistics (presented in parenthesis) are calculated using robust (White) standard errors.

Table 2 Continued

	[1]	[2]	[3]	[4]	[5]	[6]
	All retail accounts with transactions	Retail accounts of split purchasers	All retail accounts with transactions	Retail accounts of split purchasers	Retail accounts of split purchasers	Retail accounts of split purchasers
Model:	Negative binomial	Negative binomial	Logit	Logit	GLM with Logit link	OLS
Dependent variable:	*# of suspicious splits purchased*	*# of suspicious splits purchased*	*Dummy for suspicious split purchased*	*Dummy for suspicious split purchased*	*Suspicious split ratio*	*Suspicious split ratio*
Wealth	-0.090	-0.017	0.912	0.962	0.948	-0.007
	(-17.54)	(-3.54)	(-17.05)	(-6.15)	(-7.86)	(-8.39)
Return performance	-1.583	-1.249	0.078	0.149	0.312	-0.166
	(-6.63)	(-4.75)	(-10.47)	(-5.73)	(-3.30)	(-4.08)
# months since account open	-0.086	-0.039	0.912	0.958	0.994	0.000
	(-21.81)	(-11.23)	(-21.81)	(-9.05)	(-3.14)	(0.09)
# of stocks bought			1.138	1.051	1.003	0.001
			(54.07)	(20.22)	(4.26)	(3.99)
# of transactions	0.063	0.018				
	(52.16)	(30.61)				
# of stocks held	0.005	0.004	1.013	1.005	1.000	0.000
	(5.78)	(4.43)	(3.52)	(4.41)	(0.03)	(0.21)
Age	-0.004	-0.002	0.994	0.999	1.001	0.000
	(-4.42)	(-3.04)	(-5.91)	(0.99)	(0.90)	(1.03)
Female	-0.097	-0.056	0.908	0.946	0.989	-0.002
	(-5.14)	(-3.28)	(-4.85)	(-3.43)	(-6.43)	(-3.78)
Intercept	3.565	1.125	37.263	1.960	0.547	0.240
	(65.07)	(22.04)	(63.06)	(9.97)	(-8.38)	(27.63)
Pseudo_R^2	0.067	0.024	0.068	0.013	0.002	0.002
Observations	123,160	35,716	123,160	35,716	35,716	35,716

Table 3

Abnormal returns around dividend announcements

This table reports the average buy-and-hold abnormal returns around dividend announcements. The average buy-and-hold abnormal return is calculated as the buy-and-hold return minus the size-decile benchmark where t=0 is the calendar day of the split announcement. Panel A (B) reports the monthly (daily) abnormal returns around dividend announcements. Dividend/no split is the sample of dividend announcements and are not concurrent with a split announcement. Dividend increase/no split are dividend announcement that increased in RMB amount from the prior dividend and are not concurrent with a split announcement. Dividend+split are concurrent dividend and stock split announcements. Dividend increase+split are concurrent dividend increases and stock split announcements. *t*-statistics (presented in parenthesis) are calculated using robust (White) standard errors and clustered each calendar month. The sample period is from 1999/01 to 2015/06.

Panel A. Monthly abnormal returns around split announcements

			[-3 to -1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
No split sample							
Dividend only	10252	mean	0.52	-0.26	-1.06	-3.21	-4.68
		t-stat	(1.49)	(-1.59)	(-3.19)	(-2.85)	(-3.50)
Dividend increase only	5474	mean	1.20	0.07	-0.78	-1.07	-1.86
		t-stat	(3.37)	(0.39)	(-2.27)	(-0.82)	(-1.24)
With split sample							
Dividend + split	2521	mean	3.26	4.40	2.17	0.01	7.23
		t-stat	(5.02)	(12.13)	(2.80)	(0.01)	(3.68)
Dividend increase + split	1763	mean	3.95	4.80	2.56	-2.52	5.59
		t-stat	(5.19)	(12.40)	(2.80)	(-1.29)	(2.94)

Panel B. Daily abnormal returns around split announcements

	N		[-10,-2]	[-1,+1]	[+2,+10]
Dividend/no split	10252	mean	0.47	-0.56	-0.03
		t-stat	(3.93)	(-8.08)	(-0.21)
Dividend increase/no split	5474	mean	0.65	-0.44	-0.02
		t-stat	(6.03)	(-4.49)	(-0.15)
Dividend + split	2521	mean	2.42	1.86	0.05
		t-stat	(9.73)	(12.37)	(0.24)
Dividend increase + split	1763	mean	2.75	2.03	0.11
		t-stat	(10.96)	(11.41)	(0.50)

Table 4

Post earnings announcement drift in China

This table presents average buy-and-hold abnormal returns of stocks around earnings announcements in the China market. The average buy-and-hold abnormal return is calculated as the buy-and-hold return minus the size benchmark. The sample period is from 2002 to 2015 since reporting of quarterly earnings begins in 2002. Panel A presents average buy-and-hold returns from day+2 to +60 of stocks sorted in quintiles based on three–day abnormal return earnings announcement. Stocks are sorted into five groups based on three-day abnormal market reaction breakpoints from the prior eight quarters of earnings announcement. The bottom row [−1,+1] reports the three-day abnormal announcement return (the sorting variable). Positive−Negative is the average difference in returns between the Positive and Negative surprise portfolios each quarter. We report the mean estimates and *t*-statistics in parentheses, testing the hypothesis of zero abnormal return.

Abnormal Returns		Positive Surprise	4	3	2	Negative Surprise	Positive−Negative
[+2,+60]	mean	0.05%	0.06%	−0.23%	−0.63%	−1.12%	1.17%
	t-stat	(0.16)	(0.23)	(−1.00)	(−2.91)	(−4.70)	(2.85)
[−1,+1]	Mean	6.01%	1.46%	−0.43%	−2.39%	−6.23%	12.24%
	t-stat	(16.64)	(6.08)	(−1.81)	(−9.17)	(−19.51)	(31.84)

Table 5

Suspicious splits: Early vs. recent period

This table reports the average buy-and-hold abnormal returns around split announcements for suspicious split announcements in the early and later half of our sample period. The average buy-and-hold abnormal return is calculated as the buy-and-hold return minus the size-decile benchmark where t=0 is the calendar month of the split announcement. *t*-statistics (presented in parenthesis) are calculated using robust (White) standard errors and clustered each calendar month. The sample period is from 1999/01 to 2015/06.

	N		[-3 to -1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
1999-2010	290	mean	-4.45	5.28	0.93	-9.82	-2.61
		t-stat	(-2.39)	(5.10)	(0.69)	(-1.71)	(-0.44)
2011-2015	496	mean	-0.96	5.95	4.64	-11.58	0.74
		t-stat	(-0.60)	(4.50)	(2.31)	(-3.03)	(0.20)

Table 6

Robustness test: Abnormal returns around suspicious split announcements using alternative benchmarks

This table reports additional robustness tests. Panel A reports the average buy-and-hold abnormal returns around suspicious split announcements calculated as the buy-and-hold return of the split announcer minus the size x EP benchmark following Liu, Stambaugh, and Yuan (2019). Panel B reports BHAR surrounding the suspicious split announcement using alternative definitions of suspicious splits. Month t=0 is the calendar month of the split announcement. t-statistics (presented in parenthesis) are calculated using robust (White) standard errors and clustered each calendar month. The sample period is from 1999/01 to 2015/06.

Panel A. Monthly abnormal returns using size x EP benchmark

	N		[-3 to -1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
Suspicious	787	mean	-1.22	5.82	3.89	-8.64	2.67
		t-stat	(-0.88)	(5.86)	(2.50)	(-2.46)	(0.79)
Regular non-SOE	925	mean	10.23	4.31	2.86	1.92	9.74
			(8.03)	(7.34)	(3.50)	(0.50)	(2.69)
Lockup expiration	146	mean	1.27	4.95	5.42	-10.88	1.71
		t-stat	(0.73)	(3.33)	(2.18)	(-2.27)	(0.37)
Atypical timing	468	mean	-7.03	6.06	4.61	-7.53	4.74
		t-stat	(-3.71)	(5.05)	(2.06)	(-1.78)	(1.12)
High accrual	344	mean	4.01	5.50	2.96	-12.22	-2.41
		t-stat	(2.55)	(4.24)	(2.39)	(-2.69)	(-0.53)

Panel B. Monthly abnormal returns of suspicious splits (alternative definitions)

	N		[-3 to -1]	[month 0]	[+1 to +3]	[+4 to +18]	[0 to +18]
Lockup expiration							
[−3 to +3]	146	mean	1.66	3.51	3.07	-12.36	-4.68
		t-stat	(0.73)	(2.62)	(1.20)	(-2.34)	(-0.86)
[–6 to +6]	181	mean	3.36	5.45	4.09	-17.29	-6.04
		t-stat	(1.79)	(4.40)	(1.98)	(-4.24)	(-1.38)
Atypical timing							
Ret [−3,−1]<15%	404	mean	-7.13	6.59	3.84	-10.79	1.31
		t-stat	(-3.41)	(4.93)	(1.82)	(-2.77)	(0.32)
Ret [−3,−1]<25%	541	mean	-8.56	5.89	3.42	-10.14	0.68
		t-stat	(-5.07)	(5.26)	(2.07)	(-2.56)	(0.17)
High accrual							
Sloan (1996)	344	mean	2.78	5.21	4.11	-7.99	2.80
		t-stat	(2.09)	(5.41)	(3.17)	(-2.36)	(0.77)

Exhibit 1

Case study of illegal market manipulation by Xu Xiang and the Zexi Investment Company

We provide a case study of the illegal market manipulation by the Zexi Investment Company, whose manager, Xu Xiang, was convicted of insider trading in 2017. We collect the 13 convicted cases of stock price manipulation, of which 11 are stock splits. Based on our classification of suspicious splits, eight of the 11 splits qualify as suspicious. The plot of the abnormal returns around the split for these events shows strong evidence of manipulation, similar to the pattern of the suspicious splits returns in Figure 1 of the main text.

Buy-and-hold abnormal returns of stocks announcing splits manipulated by the Zexi Investment Company.

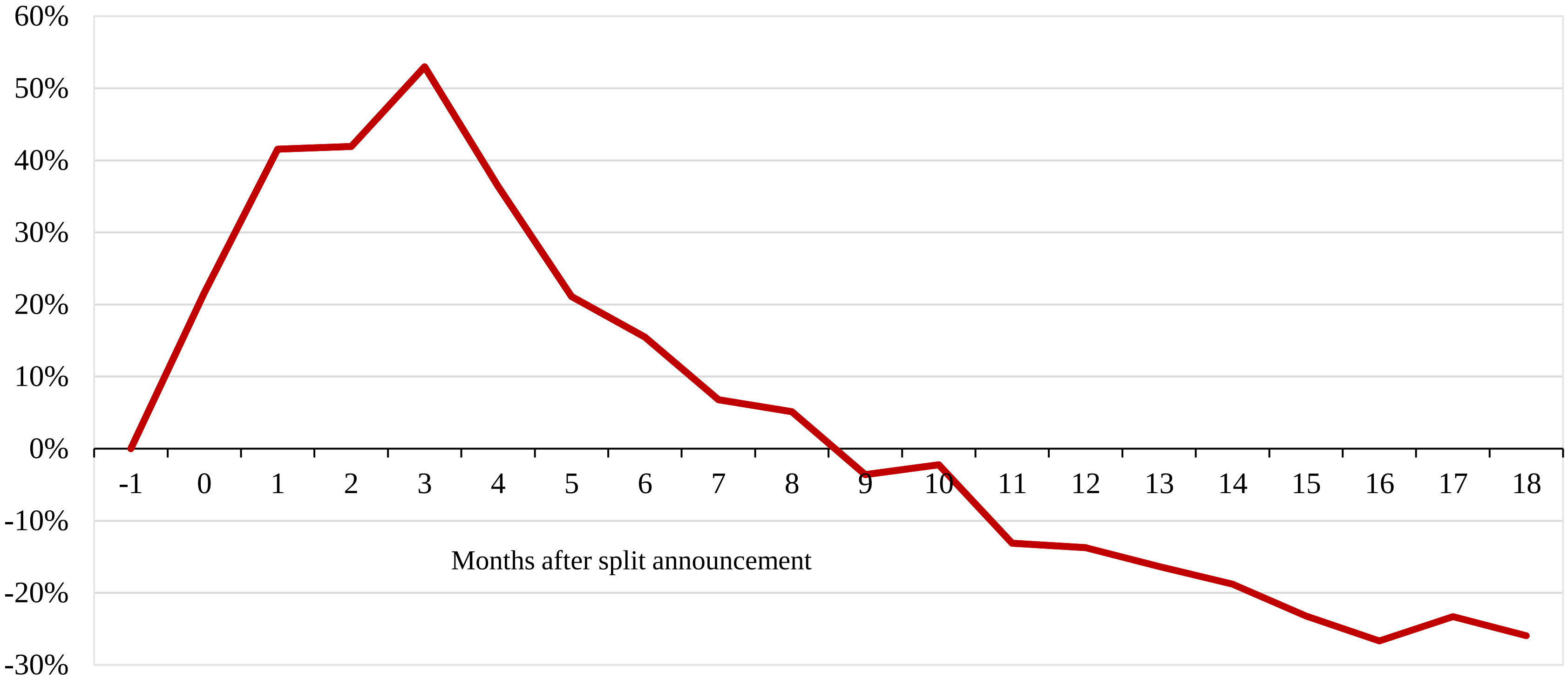


Exhibit 2

Excerpt from the legal ruling on the Zexi Investment Company scandal

纪律处分决定书（上海泽熙投资管理有限公司、上海泽熙资产管理中心（普通合伙）、徐翔、郑素贞、徐峻）

日期：2017-06-07

当事人：

上海泽熙投资管理有限公司，登记时间：2014年8月21日，登记编号：P1004404，观察会员，于2017年3月20日被注销登记。

上海泽熙资产管理中心（普通合伙），登记时间：2014年8月21日，登记编号：P1004398。

徐翔：男，1977年2月生，登记为上海泽熙投资管理有限公司总经理、法定代表人；上海泽熙资产管理中心（普通合伙）基金经理。

郑素贞：女，1952年4月生，登记为上海泽熙投资管理有限公司实际控制人；上海泽熙资产管理中心（普通合伙）执行事务合伙人。

徐峻：男，1975年11月生，登记为上海泽熙投资管理有限公司总经理助理、风控合规负责人。

根据《中华人民共和国证券投资基金法》（以下简称《基金法》）、《中国证券投资基金业协会章程》（以下简称《协会章程》）、《中国证券投资基金业协会会员管理办法》（以下简称《会员管理办法》）和《中国证券投资基金业协会纪律处分实施办法（试行）》（以下简称《纪律处分实施办法》），我会对当事人违反法律法规和自律规则的情况进行了调查。鉴于青岛市中级人民法院已于2017年1月22日判决徐翔等人犯操纵证券市场罪，徐翔等人服从判决未上诉，本次纪律处分案的事实已经《青岛市中级人民法院刑事判决书》（（2016）鲁02刑初148号，以下简称《判决书》）确认，我会据此直接作出纪律处分。

Author's English translation

From 2010 to 2015, Xu Xiang conspired with the executives or controlling shareholders of 13 listed companies to manipulate the company's stock price.

11 cases of stock trading manipulation involved the issuance of stock splits. Xu Xiang conspired with management to issue favorable news, rosy forecasts of future earnings, and announcements of popular topics including "stock split", "hepatitis B" "therapeutic vaccines", "graphene", "mobile games", "online education", "robots", "PPP", "listed companies + private equity", and "Zexi Investment Company products placard". Xu Xiang used Zexi Investment Company products and securities accounts to conduct continuous trading in the secondary market to increase the company's share price.

After the stock price increased, Xu Xiang used Zexi Investment Company products and securities accounts to purchase shares held by the above-mentioned company's stockholders in block transactions, and subsequently sold these shares in the secondary market. The stockholders of these company would sell blocks of shares to Xu Xiang below the reserve price and share the overall profits. After Xu Xiang and conspirators received payment, the agreement signed by both parties was destroyed.

In two cases of stock trading manipulation, Xu Xiang acquired non-public share issuances (private placements) jointly with the controlling shareholders of the listed company (or on behalf of others). For example, the case of Oriental Jinyu, Xu Xiang and conspirators made 9.338 billion yuan in illegal profits (based on holding of 144 million shares of as of August 18, 2015) from discounts from block trades and transactions in the secondary market.