The Chinese Stock Splits Puzzle: A Behavioral Signaling Explanation

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Abstract

We propose a behavioral signaling explanation to understand the puzzling positive announcement effects of stock splits. There are two key behavioral ingredients in our model. First, investors suffer from nominal price illusion and believe low-priced stocks to have greater price appreciation potential. Second, investors are loss-averse and will be particularly disappointed if a firm's ex-post performance falls short of expectation. In a separating equilibrium, only managers with favorable private information will use stock splits to signal. Using a comprehensive sample of stock splits in Chinese A-share market over the period of 1998 to 2017, we find supporting evidence: (1) stock splits elicit positive announcement returns and the effect is stronger among small firms held by more retail investors and with analyst coverage; (2) splits raise analysts' expectation about firms' future fundamentals; (3) splitting firms with subpar ex-post performance experience returns lower than similarly underperforming firms without undergoing splits.

Keywords: Stock split, behavioral signaling, nominal price illusion, loss aversion
JEL Classifications: G35, G40, G41

1. Introduction

Stock splits have been a puzzling corporate phenomenon for a long time. As a seemingly cosmetic corporate action, stock splits have no real effect on firms' cash flows and fundamentals, yet are frequently associated with positive announcement returns (Fama et al., 1969; Grinblatt et al., 1984; Lamoureux and Poon, 1987). The positive market reaction to stock splits does not seem to be driven by investors' overreaction or attention-driven price pressure, as studies document positive long-run return drift following splits (Ikenberry, Rankine and Stice, 1996; Ikenberry and Ramnath, 2002).

Two leading explanations have been proposed to explain the positive announcement returns associated with stock splits. First proposed by Fama et al. (1969) and Grinblatt et al. (1984), the "signaling" explanation argues that stock splits could convey managers' (private) favorable information regarding firms' future performance to outside investors. Evidence supporting the signaling explanation is documented by Asquith et al. (1989), Mcnichols and Dravid (1990), and Louis and Robinson (2005), who find that splits are associated with better future firm fundamentals such as earnings and profitability. However, the exact channel through which signaling works is unclear in those studies, because unlike other corporate actions, splits are almost costless and firms without favorable information could mimic splitting firms and send false signals to market.[1]

The second explanation, the "optimal trading range" hypothesis (Lakonishok and Lev, 1987; Dyl and Elliott, 2006), also finds mixed evidence in the literature. The idea is that a firm

[1] Exceptions include Brennan and Copeland (1988) and Ikenberry, Rankine and Stice (1996a; 1996b). Brennan and Copeland (1988) argue that splits are costly because the fixed component of brokerage commissions increases the per-share trading costs for low-priced stocks. Ikenberry, Rankine and Stice (1996a; 1996b) argue that stock splits reduce firms' financial flexibility.

with a high share price could improve the liquidity and marketability of its stock by lowering the price through splits, as many small retail investors are constrained to purchase low-priced stocks only. In an incomplete capital market (Merton, 1987), broadening the shareholder base of a stock could effectively reduce the discount rate demanded by investors and increase firm value. However, empirical evidence that stock splits lead to improved liquidity and marketability is inconclusive.[2] Some studies even find that splits increase bid-ask spreads (Copeland, 1979; Conroy et al., 1990) and return volatility (Ohlson and Penman, 1985; Koski, 1995), suggesting that splits could decrease liquidity. Baker and Gallagher (1980) claim that managers use splits to increase ownership by individual investors, but Szewczyk and Tsetsekos (1995) report that institutional ownership increases after a split.

In this paper, we propose a behavioral signaling explanation for stock splits, motivated by Baker and Wurgler (2012) and Baker, Mendal, and Wurgler (2015). The key difference between the standard signaling and behavioral signaling approaches is that the former relies on destroying real firm value for the signal to be credible, which is rejected by managers in survey (Brav et al., 2005). Under the behavioral signaling framework, a signal could be credible without destroying firm value, as long as there are some psychological costs imposed on investors when firms engage in false signaling.

In our behavioral signaling model, investors believe that low-priced stocks have higher growth potentials than high-priced stocks (Birru and Wang, 2015; 2017), or they have share splitting-related optimism. Due to loss aversion, however, they will also be particularly

[2] Lamoureux and Poon (1987) and Maloney and Mulherin (1992) document that splits increase the number of stockholders and the number of trades, but there is little evidence that splits lead to increased trading volume (Lakonishok and Lev (1987), Lamoureux and Poon (1987), Conroy et al. (1990)).

disappointed when the firms' realized performance falls short of expectation.[3] Firm managers, with an objective to maximize weighted-average of short-run stock prices and long-run firm value, trade off the costs and benefits when deciding whether to split shares. A stock split can boost investors' expectation of the firm's growth potential and short-run stock price, but may also cause disproportionally lower stock returns if the firm underperforms in the future. In equilibrium, only managers with favorable private information about firm fundamentals make stock splits, and investors correctly infer splits as a signal of positive information. A separating equilibrium can be sustained because firms splitting shares without favorable information have a higher likelihood of falling short of investors' expectation, which will lead to significantly lower stock returns in the future. Simply put, investors' psychological costs due to loss aversion prevent low-quality firms from mimicking high-quality firms through stock splits.

Using a comprehensive sample of stock split events in China from 1998 to 2017, we test the novel predictions of the behavioral signaling model. Several institutional features of the Chinese stock market make it particularly suitable for testing the behavioral signaling model. First, unlike the U.S. market where institutional investors dominate, the Chinese stock market has a larger proportion of retail investors (Carpenter, Lu and Whitelaw, 2018), who are arguably more subject to various behavioral biases such as loss aversion and are inclined to several misconceptions about stock splits. Thus, the underlying assumptions of our behavioral signaling model are more likely to hold in China. Second, brokerage commissions in the Chinese market are a fixed percentage of transaction value and are independent of the nominal share price. This unique feature helps rule out the signaling model of Brennan and Copeland

[3] Loss aversion arises because investors may use the pre-split stock price as a reference point.

(1987) and the information production theory of Brennan and Hughes (1990), both of which rely on the dependence of the brokerage commission rate on nominal share prices. Third, stock splits in China are unlikely to be associated with tax option, as selling loser stocks is not allowed to deduct taxable income. This can help rule out the explanation of tax option value for stock splits (Lamoureux and Poon, 1987). Last but not the least, while the frequency and importance of stock splits is declining in the U.S. stock market (Minnick and Raman, 2014), the Chinese market has recently experienced a boom in stock splits, which is worth investigating on its own.

We first document a significant and positive announcement effect for stock splits in the Chinese stock market. Using various expected return benchmarks, we find that stock splits are associated with three-day cumulative abnormal returns (CAR (-1, +1)) of 2% that are highly significant. The three-day window likely underestimates the magnitude of the announcement returns as there is a large price run-up of 2% to 2.5% before the announcement.

The positive announcement returns do not seem to be driven by investor overreaction or attention-driven price pressure (Seasholes and Wu 2007; Barber and Odean 2008). The post-announcement cumulative abnormal returns (CAR (2, 10) or CAR (2, 15)) are either significantly positive or indifferent from zero. Using both a buy-and-hold abnormal return (BHAR) approach and the calendar-time portfolio approach, we find a significant return drift in the three years following stock splits. In other words, investors appear to underreact to the favorable information conveyed by stock splits, which is consistent with the literature based on US sample (Ikenberry and Ramnath, 2002). The economic magnitude is non-trivial. For example, the cumulative buy-and-hold abnormal return starting from 1 month after stock splits and hold for 3 years is in the range of 11.8% to 35.5% and is highly significant based on the bootstrapped p-value. Similarly, the estimated alphas of the splitting stocks based on the calendar-time portfolio approach are either significantly positive or insignificant, suggesting that the positive announcement returns are permanent and driven by the incorporation of new information into stock prices.

As stock splits in China are commonly announced in firms' profit distribution plans and concurrent with their semi-annual or annual reports, we examine whether the split announcement returns could be explained by confounding events such as earnings or dividends announcements. In panel regressions controlling for the change of earnings and dividends, firm characteristics, event date and firm fixed effects, we still find significantly positive announcement returns in the range of 2.5% to 4%. This result suggests that the split itself conveys new information, beyond the information contained in earnings and dividends announcements. Moreover, we directly examine the fundamentals of splitting firms and find that splitting firms have higher profitability and sales growth compared to non-splitting firms in the split year and two years after the split.

After establishing the robustness of positive announcement returns associated with stock splits, we test several novel predictions of the behavioral signaling model. First, our signaling model predicts that stock splits effectively raise investors' expectation of splitting firms' fundamentals. Using analysts' consensus earnings forecast as a proxy for investors' expectation about firm fundamentals, we find supporting evidence. Second, stock splits are credible signals in our model because loss-averse investors will be particularly disappointed when firms' future performance falls short of expectation. To operationalize this idea, we use below industry-average ROA in the post-split periods to indicate firm underperformance and interact with a split event dummy. We find that long-run buy-and-hold abnormal returns are significantly lower when the splitting firm experiences below industry-average ROA, compared with similarly underperforming firms without undergoing stock splits. In terms of economic magnitude, 3-year buy-and-hold abnormal returns are 9.9% lower when the non-splitting firm underperforms ex-post, while the number is 23.2% lower when it is a splitting firm. Third, we test several cross-sectional predictions of the behavioral signaling model. We find the signaling effect of stock splits is more pronounced among small stocks held less by institutional investors, consistent with prior studies that retail investors (rather than institutional investors) mainly subject to nominal price illusion (Kumar, 2009). The announcement effect is also stronger for splitting firms with fewer analyst coverage, consistent with the idea that signaling is more informative when there is less public information available for the firms. Lastly, the announcement return is positively related to not only the decision to split or not, but also the split ratio chosen by managers, consistent with our model that managers with more favorable private information use a larger split ratio to send a stronger signal to investors.

We conduct several tests to rule out alternative theories of stock split. First, the signaling model of Brennan and Copeland (1988) argue that stock splits are costly because the fixed cost element of brokerage commissions increases the per-share trading costs of low-priced stocks. We can easily rule out this explanation using our setting because brokerage commission in China is a fixed percentage of transaction value, and independent of stock prices. The "optimal trading range" hypothesis argues that by restoring price to a normal trading range, stock splits can improve liquidity and marketability, thus increasing firm value. To rule out this alternative, we control for the change of stock liquidity and investor visibility around splits, and find similar announcement effects. To further rule out this alternative, we conduct a cross-sectional test based on the pre-split share prices. According to the "optimal trading range" hypothesis, the improvement in liquidity and marketability associated with a lower price should be larger for stocks with higher pre-split share prices, as these stocks benefit the most from the enlarged investor base. However, we find exactly the opposite result that the split announcement returns are more pronounced for splitting firms with lower pre-split share prices. This is more consistent with the behavioral signaling explanation as investors suffering from nominal price illusion believe low-priced stocks more likely to appreciate than high-priced stocks (Birru and Wang 2015).

The contributions of our paper are twofold. First, we provide a new explanation for the stock split puzzle, which is different from the traditional optimal trading range theory and classical signaling theories such as the information production theory of Brennan and Hughes (1990) and the financial flexibility argument proposed by Rankine and Stice (1997a; 1997b). Our behavioral signaling explanation squares well with the Chinese stock split setting. Although it may not be completely generalizable to other markets, it still offers a new way of rationalizing this puzzle.

Second, our paper extends the idea of Baker and Wurgler (2013) and Baker, Mendel and Wurgler (2015) to stock splits, another important corporate event. Baker, Mendel and Wurgler (2015) propose a behavioral signaling theory to explain the dividends stickiness puzzle. However, unlike stock splits, cash dividends payout is a more costly corporate action and thus harder to differentiate with classical signaling theories. In addition, the Chinese stock market offers a better laboratory than US market to test behavioral signaling theories as less sophisticated retail investors dominate the Chinese market. Our results that stock splits could be well explained by behavioral signaling model show the promise of applying the same framework in other settings.

The rest of the paper proceeds as follows. Section 2 describes the institutional background of stock splits in China. Section 3 outlines a simple behavioral signaling model for stock splits. Section 4 details our data and presents summary statistics. Section 5 presents the main empirical results. Section 6 rules out several alternatives and conduct robustness checks. Section 7 concludes.

2. Institutional Background

2.1 Stock Splits in China

In China, except for very few special cases, the par value of all tradable stocks is 1 RMB per share, and it's a convention that a firm keeps the par value unchanged after being publicly listed. Therefore, unlike in the U.S., listed firms in China do not split shares directly; instead, they employ two indirect methods. The first is to pay stock dividends out of retained earnings, and the second is to issue new shares out of capital surplus. Under both methods, the outcome is the same as a direct stock split, with increased number of shares outstanding and reduced nominal share prices. The implementation cost of both methods are trivial. For each newly issued share, typically 1 RMB would be deducted from retained earnings or capital surplus as the par value of most stocks in China is 1 RMB per share. The main difference between the direct and indirect split is accounting treatment. In the case of direct stock split, no accounting treatment is needed. In the indirect cases, either retained earnings or capital surplus are deducted to increase the capital stock. However, just like direct stock splits, neither stock dividends nor converting capital surplus into new shares has any real effects on firms' fundamentals, because the accounting treatment of indirect splits only involves adjustments among several sub-categories of shareholders' account.

Although stock splits have no direct effects on firms' fundamentals from an economic perspective, they are very prevalent in the Chinese stock market. Table 1 lists the number of stock splits events from January 1998 to June 2017; about 10% to 25% of all listed firms implement stock splits each year. It is puzzling that a seemingly cosmetic corporate action is so widespread in China.

2.2 Investors' Misperception about Stock Splits

Unlike major developed markets, the Chinese stock market is dominated by retail investors without sufficient finance and accounting knowledge. At the end of 2016, retail investors own more than 99% of all brokerage accounts and conduct more than 85.65% of total trading in the market (Shanghai Stock Exchange Statistical Annual 2017). As the trading behavior of retail investors is often driven by attention-grabbing events (Seasholes and Wu, 2007; Barber and Odean, 2008), a commonly held view in China is that firms viciously take advantage of the favorable market reaction to stock splits to extract private benefits.[4]

Why would nominal share prices and stock splits matter to investors? One possibility is

[4] The conspiracy viewpoint represents the mainstream view on stock splits in China, and is partially supported by some anecdotes and academic study. For example, Titman, Wei and Zhao (2017) find that retail investors are net buyers during the split announcement period.

that investors treat low-priced stocks as lotteries (Kumar, 2009) because they tend to overestimate the upside potential of such stocks (Birru and Wang, 2016). In the Chinese stock market, other misperceptions about stock splits besides the nominal price illusion are widespread among retail investors.

The first misperception is that investors often view stock splits as a form of profit distribution similar to cash dividends, although in the case of splits, nothing is actually paid out of the firm. For example, according to Baidu Baike, China's version of Wikipedia, stock splits is a form of corporate payouts. Popular financial websites, such as Sina Finance and Hexun.com[5], often categorize both stock splits and cash dividends as payouts and exhibit them in the same place.

The timing a company announces stock split could further amplify this misperception. In practice, both cash dividends and stock splits are disclosed in the annual or semi-annual profit distribution proposals, which could give investors the impression that stock splits and cash dividends are equivalent means of distributing profits. The terminology a firm uses to describe stock split could also be misleading. For example, on May 19, 2003, Vanke declared that for every 10 outstanding shares, an investor would get 2 CNY cash dividends and 10 new shares from capital surplus. This kind of statement conveys illusive information to Vanke's shareholders that their stock investments earn lucrative profits, although only 0.2 yuan per share is the actual profit distributed to them.

The second misperception about stock splits is that many retail investors believe stock prices after splits will go back to the pre-split level. According to this misperception, after stock

[5] Both of Sina Finance and Hexun.ccom are leading financial portal website in China.

splits, the pre-split share price becomes the natural anchoring point, toward which the post-split share price would be pulled back eventually.[6] This suggests that Chinese investors' view towards stock price and stock splits differ a lot from the conventional view in U.S. In U.S., firm tends to split shares when stock price deviates from the optimal trading range. In other words, it is the post-split share price not the pre-split price that is more preferred by the firm and its investors. However, in China, the pre-split price is what investors consider stock price should be.

Although investors' bias associated with stock splits may result from a variety of reasons, a clear prediction is that all of them lead to more optimistic expectation about firms' future performance after stock splits.

3. A Simple Behavioral Signaling Model

3.1 Overview of Existing Signaling Models

The idea that firms use stock splits to convey new information dates back to Fama, Fisher, Jensen and Roll (1969). Although many studies document empirical evidence supporting the signaling hypothesis (Grinblatt, Masulis and Titman, 1984; Lakonishok and Lev, 1987; Asquith, Healy and Palepu, 1989; Mcnichols and Dravid, 1990), the exact channel that makes stock splits credible is still unsettled. As the implementation cost of stock splits is trivial, standard signaling models often have a difficult time to conjecture the mechanism that makes stock splits a credible signal.

[6] It is difficult to pinpoint where this illusion comes from. One conjecture is investors' habits of using technical analysis. Technical analysis tends to search specific patterns from past price and volume and regard such patterns as predictive signals for future price movement. The price drop caused by ex-right adjustment is believed to be an indicator that ex-right price would revert to cum-right price in the near future.

One such explanation is based on transaction costs. Brennan and Copeland (1988) argue that the commission rate of per dollar transaction is inversely related to nominal share price, which makes splits a credible signal. Brennan and Hughes (1991) develop a model in which the dependence of brokerage commission on share price provides incentives for financial analysts to supply information, and Chemmanur, Hu and Huang (2015) documents evidence supporting their theory. However, the transaction cost argument is unlikely to hold in China, because brokerage commission is usually a fixed percentage of the transaction value, and independent of share price.

Rankine and Stice (1997a; 1997b) propose another type of cost associated with stock splits. They notice that the accounting treatment of stock splits in US reduces a firm's financial flexibility, since debt covenants often impose restrictions on firms' ability to pay cash dividends out of retained earnings. Consistent with their hypothesis, Rankine and Stice (1997a; 1997b) find that stock splits are associated with larger market reactions when the accounting rules governing stock splits are more stringent. However, the financial flexibility hypothesis are unlikely to be applied in China for two reasons. First, in China, the new shares generated by stock splits mainly come from capital surplus not from retained earnings, and the accounting rule for transferring capital surplus is very loose.[7] In addition, unlike retained earnings, capital surplus cannot be used to pay cash dividends in China.

[7] Firms usually have abundant capital surplus because the IPO offering prices are usually much higher than the par value of a stock. For example, if the IPO price of a firm is 21 RMB, then the newly issued shares in the IPO process make it possible to issue a 20 for 1 split.

3.2 Model Setup

Motivated by Baker and Wurgler (2013) and Baker, Mendel and Wurgler (2015), we use a simple behavioral signaling model to provide an equilibrium explanation for the stock split puzzle. The intuition of the behavioral signaling explanation is that although investors' misperception towards stock splits could result from many reasons, they all tend to raise investors' expectation about the splitting firms' future performance.[8] This motivates all firms to use stock splits in the absence of the costs of false signaling. To facilitate a separating equilibrium, we introduce the well-known loss-aversion preference for investors, that is, investors feel more pain when they suffer loss relative to a reference point than experiencing joys when they have gains. Specifically in the context of stock splits, although splits raise investors' expectation, investors will also be particularly disappointed when the splitting firms' ex-post performance falls short of expectation. Because managers care about both short-run and long-run stock prices, those without favorable private information will not split.

Our model contains two players, a manager, who want to trade off the short term and long-term stock prices, and a representative naïve investor who has biased expectations about splitting stocks and are loss averse. The manager manages a firm with an uncertain value V that is realized in the second period. The manager also receives a private signal e about V in the first period, but this signal is only partially informative, and an unobservable shock ε will affect V. For simplicity, we assume that V is determined by adding up e and ε.

[8] If investors believe low-priced stocks have more upside potentials (Birru and Wang, 2016), they would have higher price appreciation expectation after stock split. If investors treat stock split and cash dividend as equivalent payouts, then share splitting is naturally considered to indicate superb performance and promising future. If investors believe the cum-right stock price would pull the ex-right price back to its historical level, then share splitting is almost identical to a signal of investing value and upward tendency, investors will of course, give up their outdated opinions and reform a higher expectation upon a stock split event.

$$V = e + \varepsilon \quad (1)$$

Here e is the manager's private information about firm value, unobservable to outside investors, so the manager needs to choose a stock split ratio s to convey his private information. In our model, both e and ε are random variables from outside investors' perspective, with probability functions f_e and f_ε defined over support $[0, \overline{e}]$ and $[0, \overline{\varepsilon}]$, respectively. F_e and F_ε are the corresponding cumulative density functions for e and ε.

For various reasons we discussed above, the naïve investor believes splitting firms have higher growth potential and better fundamentals. Whenever he sees a stock split event, he raises the expectation of the splitting firm's value by as, where a (a>0) is a parameter used to measure the degree of this naïve investor's optimism about stock splits.

The representative investor has a non-standard utility function, where utility is defined not with respect to the level of wealth but relative to a reference point. In addition, the investor is loss averse so that a given loss generates larger utility loss than an equivalent gain. Specifically, the investors' utility function is taking the form of the following equation:

$$U_i = V + b\,(V - V^E)\,I\,(V < V^E) \quad (2)$$

In the above formula, I (.) is an indicator function that takes the value 1 if the condition in the bracket is satisfied and 0 if not. b is a positive constant reflecting the asymmetry of gain and loss on utility. V^E is investors' expectation of firm value after seeing stock splits, and it is an increasing function of the split ratio s. Without loss of generality, we use the simple linear function to reflect the impact of stock splits on the investors' expectation.

$$V^E = as \quad (3)$$

Manager's utility is determined by both the current stock price and the future stock price.

Given his private information e, the manager chooses a split ratio s to maximize the weighted average shareholder value. Baker, Mendel and Wurgler (2015) use a similar method to model manager's optimization problem when deciding dividends payout.

$$s = argmax_s\ E[\alpha\ \mu(s) + \beta\ U_i \mid e] \quad (4)$$

where $\mu(s)$ is investors' expectation of firm value conditional on receiving the stock split signal s. Plug (2) and (3) into (4), we could get the following formula:

$$\begin{aligned} s &= argmax_s\ \alpha\mu(s) + \beta b\int_0^{as-e}(e+r-as)\ f_\varepsilon(r)dr\ I(as-e>0) \\ &= argmax_s\ M\mu(s) + \int_0^{as-e}(e+r-as)\ f_\varepsilon(r)dr\ I(as-e>0) \quad (5) \end{aligned}$$

In (5), M is a simplified parameter equals $\frac{\alpha}{b\beta}$, which ensures the equivalence of the optimization problem.

3.2 Equilibrium Solutions

We use Perfect Bayesian equilibrium (henceforth PBE) as the equilibrium concept. In PBE, the following two conditions must be satisfied at the same time:

(1) Given manager's private information e, belief function $\mu(s)$ and the effect of splits on naïve investor's utility U_i, s maximizes manager's utility.

(2) Belief consistency. In equilibrium, the market makes a correct conjecture, in other words, $e = \mu(s)$.

Lemma 1. In equilibrium, $\mu(s)$ is a weakly increasing function of the split ratio s.

We prove Lemma 1 by contradiction. Suppose not, if there are splitting ratios s_1 and s_2, with $s_1 < s_2$, but $\mu(s_1) > \mu(s_2)$. Denoting e_1 and e_2 as the firms' private information with corresponding split ratios s_1 and s_2, then according to incentive comparability condition, the following two inequalities must hold.

$$M\mu(s_1)+\int_0^{as_1-e_1}(e_1+r-as_1)\,f_\varepsilon(r)dr\;I(as_1>e_1)\ge M\mu(s_2)+\int_0^{as_2-e_1}(e_1+r-as_2)\,f_\varepsilon(r)dr\;I(as_2>e_1)$$

$$M\mu(s_2)+\int_0^{as_2-e_2}(e_2+r-as_2)\,f_\varepsilon(r)dr\;I(as_2>e_2)\ge M\mu(s_1)+\int_0^{as_1-e_2}(e_2+r-as_1)\,f_\varepsilon(r)dr\;I(as_1>e_2)$$

However, the second one could not be true. On the one hand, by assumption we have $\mu(s_1) > \mu(s_2)$, on the other hand, since $s_1 < s_2$, to make the inequality plausible, the following inequity $\int_0^{as_2-e_2}(e_2+r-as_2)\,f_\varepsilon(r)dr\;I(as_2>e_2)>\int_0^{as_1-e_2}(e_2+r-as_1)\,f_\varepsilon(r)dr\;I(as_1>e_2)$, must be true. However, because for any e, the function $\int_0^{as-e}(e+r-as)\,f_\varepsilon(r)dr\;I(as>e)$ is not increasing in s, which leads to a contradiction, so $\mu(s)$ cannot be decreasing in s. That explains why a firm has the incentive to do stock splits, because in the short run, the firm could be recognized by the market as a higher type if the split ratio is larger.

As $\mu(s)$ is weakly monotonic, we could take the derivative with respect to s in manager's utility maximization problem and derive the following first-order condition:

$$M\mu'(s)-aF(as-e)\,I(as>e)=0 \quad (6)$$

Plugging in the belief consistency condition $e = \mu(s)$ into the above equation, we could get the following differential equation:

$$Me'-aF(as-e)\,I(as>e)=0 \quad (7)$$

It is easy to show that when the indicative function $I\,(as > e)$ takes different values, the differential equation has different forms of solutions.

When the split ratio s is lower compared to e, and $as < e$, then $\mu(s)$ is a constant. This result is reasonable, because when s is smaller than $\frac{e}{a}$, share splitting is not a credible signal, as it incurs no cost.

When the split ratio s is large enough satisfying $s \ge \frac{e}{a}$, equation (7) has a linear solution, and our following analysis will focus on this particular solution.

Equilibrium. For a manager with private information *e*, his choice of split ratio *s* is given by

$$s(e) = e / a + c \quad (8),$$

where *c* is a constant that solves $F_\varepsilon(c) = \frac{M}{a^2}$. Equation (8) provides the separating equilibrium of the behavioral signaling model.

3.3 Empirical Predictions

The separating equilibrium implies that, everything else being constant, a larger stock split ratio *s* is associated with the manager's more favorable private information *e*. This leads to the following prediction:

Prediction 1. The market reaction to stock splits should increase with the split ratio.

In addition, the behavioral signaling model has distinctive predictions that are not shared with standard signaling theories. From (8), we could see that the marginal effect of one unit split ratio depends on the parameter *a*, which measures the degree of investors' optimism on firms undergoing splits. When *a* is larger, the same split ratio *s* could raise investor's expectation $V^E = as$ to a higher level. In other words, for a firm manager with private information *e*, a lower split ratio *s* is sufficient for him to send a credible signal. As a result, our behavioral signaling equilibrium offers the second empirical prediction:

Prediction 2. Given the stock split ratio *s*, firms with larger parameter *a* should be associated with larger market reactions when announcing splits.

4. Data and Methodology

4.1 Sample Selection and Summary Statistics

We use a comprehensive sample of stock split events in China's A-share market from 1998 to 2017 to conduct empirical tests. In most cases, Chinese firms announce stock splits in profit distribution proposals and are concurrent with financial reports. Because annual and semi-annual profit distribution plans differ in importance and formality, we only consider annual profit distribution proposals in the analysis.[9]

Our initial sample includes all stock split events (annual profit distribution proposals) from all publicly listed companies in the Shanghai Stock Exchange and Shenzhen Stock Exchange. We then exclude firms listed for less than 12 months and firms in the financial industry. To avoid the influence of other corporate events, we further exclude observations when stock trading is suspended during the [-10, 1] event window.[10] We also exclude observations with missing variables in the regression. Except for stock returns and the *Split Ratio*, we winsorize all continuous variables at their 1st and 99th percentiles to mitigate the influence of outliers. In order to isolate the effect of stock splits from other confounding information, we include both the splitting and non-splitting stocks in the regression. All data are retrieved from CSMAR and Wind.

Table 2 presents the summary statistics of the variables used in the regression analyses. The mean of *Split Dummy* is 0.161, which is close to the percentage of splitting firms reported in Table 1. The mean of *Annual Report* dummy is 0.971, indicating that majority of profit

[9] In our sample period, there are 34,451 annual profit distribution proposals with 20,836 proposals announcing cash dividends and 6,086 proposals announcing splits. Meanwhile, the corresponding number for the semi-annual proposals is 32,236 in total, but only 744 and 856 proposals announce cash dividends and stock splits, respectively.

distribution proposals are disclosed together with the annual report. The mean of *CAR[-1, 1]* and *CAR[-10, 1]* are insignificantly different from 0.

Although not the focus of our paper, we first examine the determinants of a firm's stock split decisions. As we can see from column (1) and column (5) of Table 3, smaller firms (*LnSize*) and relatively young firms (*Age*) are more likely to conduct stock splits and split shares using a larger ratio. Firms are also more likely to split shares if they experience large price appreciation in the past 12 months (*RunUp*) and are associated with high pre-split share prices. These findings are generally consistent with the prior literature.

Intuitively, firms should have strong incentive to use stock splits to signal favorable information when the current stock price is relatively under-valued. Following D'Mello and Shroff (2000), we construct a variable *PV_DS* to measure stock misvaluation. A smaller *PV_DS* indicates that a lower current stock price relative to its intrinsic value.[11] We also adopt the approach of M/B decomposition proposed by Rhodes-Kropf, Robinson and Viswanathan (2005) and construct a variable *PV_RRV* to capture how much a firm's valuation deviates from the industry average.[12] Similar to *PV_DS*, smaller *PV_RRV* indicates more severe under-valuation. In columns (2) and (6), we find that *PV_DS* is significantly negatively associated with *Split Dummy* (*Split Ratio*), and similar pattern for *PV_RRV* is observed in columns (3) and (7).

If stock split is used as a signaling device, it should be positively associated with managers' private incentive to increase firm value. We use two variables to measure managers' private

[11] Following D'Mello and Shroff (2000), we use the residual income model to estimate the intrinsic value. We use the realized income in future 3 years to calculate residual income, and the terminal value is the average of the last two period residual income. The discount rate we use is estimated by CAPM.

[12] Following Rhodes-Kropf, Robinson and Viswanathan (2005), we regress the logarithm of a stock's market capitalization on the logarithm of its book value and net income (if positive), a dummy indicating negative net income, and leverage ratio for each industry-year and take the regression residual as the *PV_RRV* measure.

incentive to increase share prices. The first one is *Lockup Expiration*, a variable intended to capture insiders' (large shareholders or managers) diversification motives after their locked up shares become tradable. The *Lockup Expiration* dummy takes value of 1 if the predetermined IPO or Split Share Structure Reform shares expiration period is within in the t-3 to t+3 month around the split announcement month, and 0 otherwise. The second measure is *Share Pledge*. In China, a large number of controlling shareholders pledge their shares as collateral to raise fund from financial institutions. These controlling shareholders usually have strong incentives to maintain a high share price so that they could minimize the probability of facing margin call and losing control rights. Consistent with our prior, columns (4) and (8) show that both *Lockup Expiration* and *Share Pledge* are positively associated with firms' stock split decision.

4.2 Empirical Methodology

To test the prediction of the behavioral signaling model, we run the following regression:

$$CAR\ [t_1,\ t_2]_{i,t} = \gamma_i + \lambda_t + \beta\ Split\ Ratio_{i,t} + \delta'\ X_{i,t} + \varepsilon_{i,t}$$

In the above regression model, *i* and *t* indicate stock and announcement date. *CAR* is the cumulative abnormal returns within the event window [t_1, t_2], where abnormal return is measured as the raw stock return minus the corresponding (value-weighted) size and B/M ratio matched portfolio return.[13] As shown in Figure 1, stock price begins to rise several days before the event date, so we use both *CAR* [-1, 1] and *CAR* [-10, 1] as the dependent variables. When *CAR* [-1, 1] is the dependent variable, we include pre-announcement cumulative abnormal

[13] We have used alternative methods including market adjusted return, market and multi-factor models with beta estimated in the [-120, 20] pre-event to estimate expected stock returns in the event window. Our results are similar using these different measures.

returns *CAR* [-10, -2] as an additional control to account for the possibility of information leakage. γ_i and λ_t are firm and announcement date fixed effects, which are used to control for time-invariant firm heterogeneity and market-wide shocks. *Split Ratio* is the key explanatory variables, measured as the number of newly issued shares from stock split scaled by the original number of shares outstanding.

$X_{i,t}$ is a vector of control variables. We include *LnSize* (the natural logarithm of market capitalizations), *LnBM* (the natural logarithm of book-to-market ratio), and *RupUp* (past 12-months cumulative returns). These are common firm characteristics associated with future stock returns.

The common practice for Chinese firms is to announce stock splits in the profit distribution proposals, and the distribution proposal itself is usually part of the annual report. As a result, other information events may contaminate the information content of stock splits. We add *ΔDividend* and *ΔIncome* as control variables to control for concurrent information about cash dividends and earnings, respectively. We define *ΔDividend* (*ΔIncome*) as the difference between current cash dividends (net income) and previous year cash dividends (net income) scaled by the market capitalization at the end of prior year. As there are cases that profit distribution proposals are not issued concurrent with the annual report, we add a dummy variable *Annual Report* equals 1 when the stock split is disclosed in the annual report and 0 otherwise.[14] To control for the changing liquidity around splits, we add into the regression the change of illiquidity *ΔIlliquidity*, measured as the difference between the Amihud (2002) illiquidity level post ex-date and before announcement date. Illiquidity post ex-date is the

[14] When *Annual Report* takes value of 1, *ΔIncome* is defined as the earnings growth rate; when *Annual Report* takes value of 0, *ΔIncome* is set as 0.

average daily illiquidity in the [11, 70] post ex-date window, the illiquidity pre-announcement is the average illiquidity in the [-70, -11] pre-announcement window.[15]

In our behavioral signaling framework, a higher split ratio increases investors' expectation of firm fundamentals. According to the empirical prediction derived in section 2.3, the regression coefficient β should be significantly positive.

5. Empirical Results

5.1 Market Reaction to Stock Splits

5.1.1 Short-run Market Reaction

Similar to the pattern in the U.S. (Grinblatt, Masulis and Titman, 1984; Lamoureux and Poon, 1987; Mcnichols and Dravid, 1990; Ikenberry, Rankine and Sitce, 1996; Rankine and Stice; 1997a; 1997b), stock splits in China is on average associated with significantly positive market reactions. Table 4 reports the short-term market reaction to split announcement. In the first three columns, we report the abnormal returns on the day before announcement (date t=-1), on the announcement date (date t=0) and on the day after the announcement (date t=1). On average, stock splits lead to 0.7%, 1% and 0.2% of abnormal returns on date -1, 0 and 1, respectively. The magnitude of market reaction to stock split is robust and comparable using different expected return models. Summing up the abnormal returns across the three days, stock splits are associated with around 2% cumulative abnormal returns in the [-1,1] announcement window. Further investigation reveals that stock price starts to rise even before the formal announcement date, as both the [-10, -2] window and the [-5, -2] window are associated with

[15] If a firm does not make ex-right price adjustment, we assume the ex-date is 75 days after the split announcement date, which is the averaged time lag between the announcement date and ex-date.

significant positive cumulative abnormal returns. This indicates the possibility of information leakage about stock splits ahead of the formal announcement. The findings in Table 4 Panel A is generally consistent with Titman, Wei and Zhao (2017).

The positive short-run market reaction to stock splits could be consistent with either signaling models or market overreaction. Barber and Odean (2008) document that individual investors are net buyer following attention-grabbing event and that could push up stock prices temporarily. However, price pressure driven by excess attention should reverse in the subsequent trading days.[16] In the last three columns of Table 3, we report the post-event cumulative abnormal returns, and find no evidence of return reversal up to 15-trading-days post-announcement, suggesting the positive announcement returns are driven by the incorporation of new information into stock prices.

5.1.3 Long-run Market Reaction to Stock Splits

Mispricing may take a long time to be fully corrected.[17] To further examine the possibility of short-run market over-reaction, we use both the buy-and-hold abnormal returns (BHAR) and calendar-time portfolio approaches to examine the long-term market reaction to stock splits.

The key idea of BHAR approach is to compare a stock's long-run performance to the performance of a benchmark portfolio. This method more closely reflects investors' true investing experience. Following the literature, we compute the buy-and-hold abnormal returns for every splitting stock according to the following equation:

[16] Seasholes and Wu (2007) use the setting of price limit in Chinese stock market to proxy for attention-grabbing events, and document price reversal within a week.

[17] Da, Engelberg and Gao (2011) find that stock overvaluation associated with abnormal Google search gradually revert within a year. Loughran and Ritter (1995) find that IPO and SEO stocks underperform matched stocks in the subsequent 5 years.

$$BHAR_i^{[s,s+\tau]} = \Pi_{t=s}^{s+\tau}\left(1+R_{i,t}\right) - \sum_1^{n_s} \omega_{j,s} \Pi_{t=s}^{s+\tau}\left(1+R_{j,t}\right) \quad (1)$$

where i indicates splitting stock, j indicates the benchmark portfolio to which stock i is compared to. The superscript $[s, s+\tau]$ indicates that splitting stocks are held for τ months, from the beginning of month s to the end of the month $s+\tau$. For every splitting stock, we choose a benchmark portfolio that is not periodically rebalanced to avoid rebalancing bias (Barber and Lyon, 1997). n_s is the number of stocks in the benchmark portfolio, $\omega_{i,s}$ is each stock's weight in the benchmark portfolio.

We compute the mean $\overline{BHAR}$ across all the splitting stocks according to the following equation, where N is the total number of split events.

$$\overline{BHAR} = \sum_1^N BHAR_i \quad (2)$$

Since the BHAR is the difference of a τ month buy-and-hold return between a stock and a benchmark portfolio, the distribution of BHAR is often highly skewed and does not have a zero mean (Barber and Lyon, 1997). We follow the method of Brock, Lakonishok and LeBaron (1992), Ikenberry, Lakonishok and Vermaelen (1995), Ikenberry, Rankine, and Stice (1996), and draw statistical inference based on an empirically generated distribution.

For every stock announcing split at event month t, we randomly select a non-splitting stock with similar observable characteristics (for example, same industry, size and book-to-market ratio depending on the benchmark portfolio we use) in the same month. This process continues until every splitting stock is matched by a non-splitting stock. We then form a pseudo portfolio constructed using non-splitting stocks and estimate the $\overline{BHAR^p}$ in the same way as we do for the splitting stocks.[18] The above procedure is repeated for 1,000 times so as to derive 1,000

[18] For example, if we want to compare the long-run performance of splitting and non-splitting firms in the same industry, the benchmark portfolios used are the 22 valued-weighted industry portfolios. The pseudo stock for each event stock is randomly

$\overline{BHAR^p}$ s and hence the empirical distribution of $\overline{BHAR}$ under the null of no abnormal returns. The null hypothesis tested is that the event $\overline{BHAR}$ equals the mean long-run abnormal return for the 1,000 pseudo-event portfolios.

Table 5 Panel A reports the results. We use the value-weighted market return, 22 industry portfolio returns, and 25 size and B/M ratio sorted portfolio returns as the expected returns, and look at a three-year holding period [1, 36] as well as three one-year holding period BHARs. The statistic we use is p-value, which is the fraction of $\overline{BHAR^p}$ s from the empirical distribution that are larger than $\overline{BHAR}$; y_h and y_l are the 95$^{\text{th}}$ and 5$^{\text{th}}$ percentile of $\overline{BHAR^p}$ of the empirical distribution, respectively. If $\overline{BHAR}$ is lower (higher) than y_l (y_h), then splitting stocks significantly underperform (outperform) non-splitting in the long run at the 5% significance level.

Table 5 Panel A shows that splitting stocks significantly outperform the benchmark portfolio over the subsequent 36 months. This finding is consistent with evidence from the US (Ikenberry, Rankine and Stice, 1996; Desai and Jain, 1997; Ikenberry and Ramnath, 2002), indicating that investors to some extent under-react to the information contained in stock splits. The result also reveals that the return differences between splitting stocks and benchmark portfolio is largest during the first year post-split and gradually decline over time.

We also use the calendar-time portfolio approach as this method naturally addresses the cross-sectional correlation in stock returns. Under this method, the long-run performance of stock splits could be inferred from the alphas estimated from the time-series regression of

selected from the same industry. Similarly, if we want to compare the long-run performance of split and non-splitting stocks with comparable size and book-to-market ratio, we use the 25 value-weighted size and book-to-market ratio independently sorted portfolios as the benchmarks, and the pseudo stock for each event stock is randomly picked from the size and book-to-market matched portfolio.

portfolio returns on asset pricing factors.

Specifically, in each month, we select all the stocks announcing splits in the previous 36 months and form a portfolio containing all such stocks. We then hold this portfolio for 1 month and rebalance monthly to include stocks just conduct splits in the last month and remove stocks whose most recent split occurred more than 36 months ago.

Table 5 Panel B reports the calendar-time portfolio results, with the upper part showing the equal-weighted portfolio returns, and the lower part showing the value-weighted portfolio returns. Column (1) shows that the equal-weighted portfolio earns 1.5% excess returns per month, significantly at the 5% level. In the following four columns, we estimate alphas using standard asset pricing models including the CAPM, the Fama-French 3 factor model (Fama and French, 1993), the Carhart 4 factor model (Carhart, 1997), and the Fama-French 5 factor model (Fama and French, 2015). While alpha estimates are sensitive to the factor models used, they are never significantly negative. In Column (6), we follow Liu, Stambaugh and Yuan (2018) and use the CH-3 factors as the pricing model, and the alpha is insignificant. In the second to the fourth row, we select stocks conducting splits in the previous [1, 12] months, [13, 24] months and [25, 36] months, respectively. The results show that when we examine the long-run performance year by year, we do not find any evidence of return reversal. The results for the value-weighted returns are qualitatively similar as shown in the bottom part of Table 5 Panel B.

5.1.4 Regression Analyses

The portfolio analyses in the above sections, although informative, do not control for other confounding information and ignore the difference in firm characteristics between splitting and non-splitting stocks. In this section, we conduct multivariate regression analysis for both the short-term and long-term market reaction to stock splits.

In Table 6 Panel A, the key explanatory variable is the *Split Dummy*, indicating whether a firm announces stock split in the annual profit distribution proposal or not. In columns (1) and (2), we find that stock splits are associated with significant positive announcement returns, even after controlling for earnings growth (*ΔEarnings*), dividend growth (*ΔDividends*), and the change of liquidity (*Δ Illiquidity*). Stock splits are on average associated with 2.5% abnormal returns in the three-day announcement window and 4.0% abnormal returns when we consider information leakage in the pre-announcement window.

Panel B of Table 6 reports the regression results of cumulative abnormal returns on the *Split Ratio*. Column (1) shows that the variable *Split Ratio* is positively associated with three-day cumulative abnormal returns with a t-statistics as large as 20.80. Column (2) shows that the effect is even larger after taking into account the information leakage before the announcement date. The coefficient of *Split Ratio* is 0.071 when the dependent variable is abnormal returns cumulated over the [-10, 1] window, indicating that a 2 for 1 split (*Split Ratio* equals 1) on average leads to a CAR of 7.1%. This is consistent with the equilibrium prediction of our behavioral signaling model, as firms with differential degrees of private information choose different split ratios to separate from each other.

The signs of other control variables are in line with prior studies and our expectations. For example, *ΔDividends* and *ΔEarnings* are positively related to the announcement returns in column (2). The coefficient of *ΔIlliquidity* is significantly negative, implying that the improvement in stock liquidity after splits may also contribute to the positive announcement effect.[19] The significant coefficients of *LnSize* and *LnBM* are consistent with the well-known size and value effects in the Chinese stock market. The coefficient of *CAR[-10, -2]* is significantly negative, suggesting that the more information leaked before the announcement, the less is revealed on the announcement date.

We also use a propensity score matched sample to conduct regression analysis. Each year, we use the propensity score matching procedure to find a non-splitting firm that is similar to the splitting firm in a set of observable firm characteristics.[20] Columns (3) and (4) of Table 6 shows that when we use the matched sample, both the *Split Dummy* and *Split Ratio* continue to be significantly positive and the magnitudes are similar to those of the full sample. In columns (5) and (6) of Table 6, we run Fama-Macbeth (1973) regression. The *Split Dummy* in Panel A and *Split Ratio* in Panel B remain to be significantly positive.

In Table 6 Panel C, we run Fama-Macbeth (1973) regression of monthly stock returns on the *Split Dummy* and *Split Ratio* to examine the long-run performance of splitting stocks. Consistent with the portfolio result in Table 5, long-run returns of splitting stocks do not reverse but to some extent continue to rise post-split.

Overall, our evidence suggests that the positive announcement returns cannot be explained by investor overreaction or attention-driven price pressure. Instead, both the short-run market

[19] Whether stock split is beneficial or detrimental to liquidity is still inconclusive in literature (Copeland, 1979; Baker and Gallagher, 1980; Brennan and Copeland, 1988; Conroy, Hariris and Benet, 1990; Baker and Powell, 1993; Muscarella and Vetsuypens, 1996; Angel, 1997; Rozeff, 1998; Schulz, 2000; Lin, Singh and Yu, 2009). Nevertheless, in our paper, this channel at most offers a partial explanation, because the coefficient of Split Ratio is still highly significant after we control for *ΔIlliquidity*.

[20] The firm characteristics include *LnSize*, *LnBM*, *LnPrice* (the natural logarithm of last month's closing price), *ΔIncome*, *ΔDividends*, *Split Capacity* (capital surplus plus retained earnings per share, which determines the maximal split ratio), *ROA* (return on asset), *Age* (number of years that a firm has been listed), and industry affiliations (22 industries based on the industry classification of China Securities Regulatory Commission).

reaction and long-run performance suggests that firms use stock split to signal favorable private information and market (gradually) incorporates the information into stock prices.

5.2 The Fundamentals of Firms Conducting Stock Splits

Our behavioral signaling model predicts that in equilibrium, only firms with favorable fundamental information would split. This implies that splitting firms should have better fundamental performance post-split than non-splitting firms should. To test, we compare the fundamental performance of splitting firms with non-splitting firms in the years around stock split.[21] Specifically, we regress various measures of fundamental performances including return-on-assets (ROA), earnings and sales on the split dummy or split ratio, and control for several firm characteristics including size, book-to-market ratio, past 12-month stock returns, and past profitability. The results are reported in Table 7.

In Panel A, we use return-on-assets to measure firm fundamentals. Both the *Split Dummy* and *Split Ratio* are significantly positive, indicating that splitting firms are more profitable than non-splitting counterparts are. Panel B and Panel C show that splitting firms experience faster earnings and sales growth post-split. These findings are consistent with the signaling argument of Asquish, Healy and Palepu (1989) that stock split convey information about the growth of fundamentals in future. Importantly, we control for the level of past ROA in the regression, so the result is not driven by splitting firms being always more profitable. In Panel D, we use earnings surprise to measure firm fundamental and find splitting firms are associated with more favorable earnings news.

[21] For example, if a firm announced stock split in Mar, 2014 in its 2013 annual profit distribution proposal, year 2013 is coded as year 0, and 2012, 2014 and 2015 coded as year -1, +1 and +2, respectively.

Overall, the findings in Table 7 suggest that firms conducting stock splits have better fundamental performance than non-splitting firms do, both concurrently and several years into the future. The results hold for both the *Split Dummy* and *Split Ratio*, which is consistent with our signaling model that managers with more favorable private information choose larger split ratio to differentiate with others.

5.3 Testing the Key Assumptions of the Behavioral Signaling Model

One of the key assumptions of our behavioral signaling model is that stock splits could raise investors' expectation about firms' future performance. In this section, we explicitly test this assumption using analysts' consensus earnings forecast as a proxy for investors' expectation about firms' future performance. Specifically, we use the revision of analysts' consensus forecasts (*Update*) of earnings in fiscal year t+1 and t+2 around split announcement day to infer investors' belief updating. The results are reported in Table 8.

Supporting the key assumption of our behavioral signaling model, stock splits indeed raise investors' expectation about firms' future fundamentals. Column (1) shows that the *Split Dummy* is positively related to analysts' upward forecast revision of earnings in fiscal year t+1. Column (2) shows that analysts' forecast revision is increasing with the *Split Ratio*. The positive relation between analysts' forecast revision (*Update*) and *Split Ratio* is robust after correcting the endogeneity of analysts' coverage decisions using the Heckman two-stage model in Column (3).[22] Columns (4) and (5) show similar results when we use the PSM procedure[23]

[22] In the first-stage, we use *LnSize*, *LnBM*, *ΔEarnings*, *ΔDividends*, *Earnings Volatility*, *Age*, and a vector of industry dummies to predict the probability that a firm is followed by any analyst.

[23] For PSM, we use *LnSize*, *LnBM*, *LnPrice*, *ΔEarnings*, *ΔDividends*, *Split Capacity*, *ROE*, *Age* and a vector of industry dummies to predict the probability that a firm conducts stock split. This procedure is unchanged for the columns indicated by PSM without further clarification.

to make splitting and non-splitting firms comparable in observable dimensions, or using the Fama-Macbeth regression method, respectively. The result is also robust when we use analysts' forecast revision of earnings in fiscal year t+2 in column (6), or the summed forecast revisions of earnings in fiscal year t+1 and t+2 in column (7).

The second key assumption of our behavioral model is that loss-averse investors will be particularly disappointed when splitting firms' future performance falls short of expectation. To operationalize this idea, we examine whether the long-run stock returns of splitting firms are lower when they have subpar performance after the splits. We define a dummy variable *Underperform* that equals one if the realized earnings in any of the three subsequent fiscal years is below the earnings in splitting year. Alternatively, we also define *Underperform* equal to one if the splitting firm's ROA in any of the three subsequent years is below the industry average. We then regress *BHAR[1, 36]* on the *Split Dummy* (*Split Ratio*), *Underperform*, and *Split Dummy* × *Underperform* (*Split Ratio* × *Underperform*). If investors are particularly disappointed when splitting firms' future performance fall short of expectation, the interaction of *Split Dummy* × *Underperform* should be significantly negative.

Table 9 shows that the interaction terms are significantly negative, regardless of how we define underperformance and how we measure buy-and-hold abnormal returns. The coefficient on *Underperform* itself is significantly negative, suggesting that firms with poor earnings have worse stock performance. The negative coefficient on *Split Dummy* × *Underperform* suggests that splitting firms experience even lower stock returns when they have poor operating performance post-splits, compared to similarly underperforming firms without undergoing stock splits. In our behavioral signaling model, this serves as the key mechanism preventing low-quality firms from mimicking high-quality firms by using stock splits.

5.4 Cross-sectional Heterogeneity

In this section, we test several cross-sectional predictions of our behavioral signaling model. First, if managers use stock splits to signal private information, the signal should be more informative to outsider investors if there is less public information available for the firm. Second, the behavioral biases associated with stock splits should be more prevalent among retail investors. In this case, a relatively smaller split ratio is sufficient to convey the same amount of private information compared with the case when more institutional investors hold the firm. As a result, the announcement returns to the same split signal should be greater if more retail investors hold the firm.

To test the above predictions, we estimate the following regression model:

$$CAR\ [t_1,\ t_2]_{i,t} = \gamma_i + \lambda_t + \zeta\ Split\ Ratio_{i,t} \times Z_{i,t} + \delta'\ X_{i,t} + \varepsilon_{i,t},$$

where Z is a measure of firms' information environment or investor composition. Specifically, we use *LnSize* and *LnCoverage* (the natural logarithm of 1 plus the number of analysts who issue forecasts for the firm) to measure a firm's information environment. As the two proxies are positively correlated with quality of information environment, ζ in the above regression model should be negative if the first prediction is true. We use *Institutional Holdings* to proxy for investor composition, measured as the proportion of shares held by institutional investors. As this variable is negatively correlated with the parameter a we used in section 2, ζ is predicted to be negative if the second prediction is true.

We regress the split announcement returns *CAR*(-1, +1) or *CAR*(-10, +1) on the interaction of *LnSize*, *LnCoverage* and *Institutional Holdings* with *Split Ratio*, and report the regression results in Table 10. Panel A reports the regression results for the full sample. Consistent with our conjecture, the interaction terms of *Split Ratio* with *LnSize* in columns (1) and (2), with *LnCoverage* in columns (3) and (4), and with *Institutional Holdings* in columns (5) and (6) are all significantly negative. We obtain qualitatively similar results when using propensity score matched sample in Panel B and the Fama-Macbeth regression method in Panel C of Table 10.

6. Alternative Explanations and Extensions

6.1 Controlling for Other Potential Channels

Rankine and Stice (1997a; 1997b) propose that the magnitude of split announcement effect should depend on the accounting treatment of stock splits, and should be larger when the new shares are funded by retained earnings. Their argument is that a reduction in retained earnings restricts firms' financial flexibility in paying cash dividends and makes debt covenants more likely to be violated, therefore increases the cost of stock splits and makes the signal more credible. This financial flexibility explanation, however, is unlikely to hold in China. Table 1 shows that the majority of new shares issued in stock splits are funded by capital surplus, and capital surplus is not allowed to be paid out as dividends and is not related to past performance. To further rule out the financial flexibility channel, we redefine *Split Ratio* by only considering new shares funded by capital surplus, and add another variable *Retained Earnings* which is the split ratio generated by retained earnings. The result, reported in Column (1) of Table 11, shows that *Split Ratio* continues to be significantly positive.

According to the information production theory of Brennan and Hughes (1991), stock splits could motivate information intermediaries such as analysts to produce more information because brokerage commission rates is inversely related to nominal share price in the US. This explanation does not apply to stock splits in China, because brokerage commission is based on the total transaction amount and independent of share prices. Nevertheless, to address such concern, we add *ΔCoverage*, which is the change of analyst coverage before and after the stock split scaled by the equity market capitalization (in millions), as another control in column (2) of Table 11. Amihud, Mendelson and Uno (1999) point out that stock splits could increase shareholder base, enable better risk sharing, reduce discount rates and raise firm value (Merton, 1987). To account for this possibility, we add *ΔShareholders*, which is the change in the number of shareholders before and after stock splits scaled by equity capitalization in column (2).[24] The coefficient of *Split Ratio* is not affected after we add *ΔCoverage* and *ΔShareholders*.

Lamoureux and Poon (1987) and Ohlson and Penman (1985) find turnover and return volatility are affected by stock splits, respectively. We further add the change of stock turnover *ΔTurnover* and the change of return volatility *ΔVolatility* around stock splits in column (3) of Table 11. After controlling for *ΔTurnover* and *ΔVolatility*, *Split Ratio* continues to be significantly positive. Finally, in column (4), we add all the aforementioned variables in the regression, and the result is unchanged.

6.2 Cross-sectional tests based on pre-split share prices

Another popular motivation for stock splits is the "optimal trading range" hypothesis (Baker and Gallagher, 1980; Baker and Powell, 1993). According to this explanation, stock

[24] Data on analyst coverage and number of shareholders are not available before 2003, so we do not include these two variables in the main tests.

split can restore high-priced stocks to a normal trading range, and hence improve its marketability to small investors. To test this alternative explanation, we conduct a cross-sectional test based on the pre-split share price. If our findings are mainly driven by the (perceived) improvement in marketability post-split, the announcement effect of stock splits should be more positive for stocks with higher pre-split share prices, as such stocks would benefit more from the improvement in marketability by splitting to a lower price range.

To test, we add the log of pre-split price *LnPrice* (measured as the stock price at t=-11 before the split announcement) into the regression, and interact this variable with *Split Ratio*. Contrary to the prediction of "optimal trading range", Table 12 shows that the interaction terms are significantly negative in all three specifications. This result is more consistent with our behavioral signaling explanation because investors suffering from nominal price illusion believe low-priced stocks have higher growth potential than high-priced stocks (Birru and Wang, 2016). As a result, the signaling effect is predicted to be stronger when the share price is low to begin with.

6.3 Time Trend of Stock Splits in China

Our behavioral signaling model could also help explain the time trend of stock splits in the Chinese market. Figure 3 Panel A plots the time series of mean stock split ratio. The figure clearly shows an upward trend. During the years around 2000, the mean split ratio is less than 0.5, and it gradually increases to more than 1 in the year 2016, although followed by a sharp drop in 2017.[25]

[25] To protect retail investors from opportunistic corporate activities, on Apr 8, 2017, the CSRC chairman Shiyu Liu stated to take investigation on firms conducting large stock splits in the 2nd Listed Company Association Congress. After Liu's speech, some already-announced stock splits were canceled or modified to smaller split ratio, and some firms abandoned their planned stock splits. To avoid the influence of change in regulatory environment on stock splits, in Figure 3 we plot the time trend of

Contrary to the upward trend of mean split ratio, the marginal announcement effect of stock splits (Figure 3 Panel B) is decreasing and the total announcement returns per split event is generally fluctuating without a clear trend (Figure 3 Panel C). In Table 13 Panel A, we interact *Time Trend* with the *Split Ratio* to examine how the marginal announcement effect of stock splits has changed over time.[26,27] The result in column (2) reveals that, on average, the cumulative abnormal returns over [-10, 1] associated with a split ratio of 1 decrease from 12.5% in 1998 to only 4.5% in 2017. We observe a similar declining announcement effect of splits when we use a propensity score matched sample in columns (3) and (4).

To visualize the declining marginal announcement returns of stock splits over time, each year we regress *CAR*[-10, 1] on the *Split Ratio* and the same set of control variables as our baseline regression. We then plot the time series of the regression coefficient of *Split Ratio* in Figure 3 Panel B. The figure clearly indicates that stock splits elicit weaker market reaction over time for a given level of split ratio, especially after 2007.

We further classify stock split events into *Small Stock Split* (split ratio < 0.5), *Medium Stock Split* ($0.5 \leq$ split ratio <1) and *Large Stock Split* (split ratio ≥ 1) and examine how the announcement effect evolves over time for each type of split events. This result is reported in Table 13 Panel B. The declining announcement return is evident for all three types of split events. For example, column (6) shows that the announcement return of *Small Stock Split* in 1998 is 3.1%. However, the announcement returns of *Small Stock Split* in 2017 is substantially

stock splits using the whole sample period with a solid line, and plot another time trend dropping observations after Apr 8, 2017 with a dashed line.

[26] The coefficient on *Time Trend* is absorbed by the announcement-date fixed effects in the regression.

[27] We convert the years from 1998 to 2017 into an increasing step function from 0 to 1 for ease of interpretation. The coefficient of *Split Ratio* measures the announcement effect of one unit split ratio in year 1998, and the coefficient of *Split Ratio* plus the coefficient of *Split Ratio* × *Time Trend* measures the announcement effect of one unit split ratio in year 2017.

reduced to 1.2%. The cases for *Medium Stock Split* and *Large Stock Split* are similar.

How do the increasing average split ratio and declining announcement effect fit into the behavioral signaling framework? It is reasonable to believe that as Chinese stock market becomes more matured and investors more sophisticated over time, the average investors' misperception associated with nominal share prices is gradually decreasing. This corresponds to a smaller a in the model. In equilibrium, managers need to use a larger split ratio to convey the same amount of private information as before, and market reaction to stock splits of the same magnitude should decline accordingly.

However, it would be more challenging for traditional signaling theories to explain the time trend of stock splits observed here. For example, unless the direct or indirect costs of implementing stock splits are decreasing, traditional signaling theories could not easily explain why stock splits become less effective over time.

7. Conclusion

In this paper, we propose and test a behavioral signaling explanation in the spirit of Baker, Mendel, and Wurgler (2015) to understand the puzzling announcement effects of stock splits. There are two key behavioral ingredients in our model. First, investors suffer from nominal price illusion and believe low-priced stocks to have greater price appreciation potential. Second, investors are loss-averse and will be particularly disappointed when the firm's ex-post performance falls short of expectation. In equilibrium, only managers with favorable private information will use stock splits to signal their information.

We test the novel predictions of the behavioral signaling model using a comprehensive sample of stock splits in China over the period of 1998 to 2017. Our empirical evidence is largely consistent with the model. First, splitting firms have better fundamentals compared with non-splitting firms post-splits. Second, the market reacts positively to splits announcements and the announcement returns increase with the split ratio. Third, the announcement effect is more pronounced among firms that are small, held mainly by retail investors, have fewer analyst coverage, and low pre-split share prices. We also test two key assumptions of the model and find supporting evidence: (1) stock splits raise analysts' expectation about firms' future fundamentals; (2) splitting firms with subpar ex-post performances experience lower returns, compared with similarly underperforming firms without undergoing splits. Overall, our paper shows the promise of applying the behavioral approach to shed light on certain corporate events that are otherwise difficult to rationalize under rational framework.

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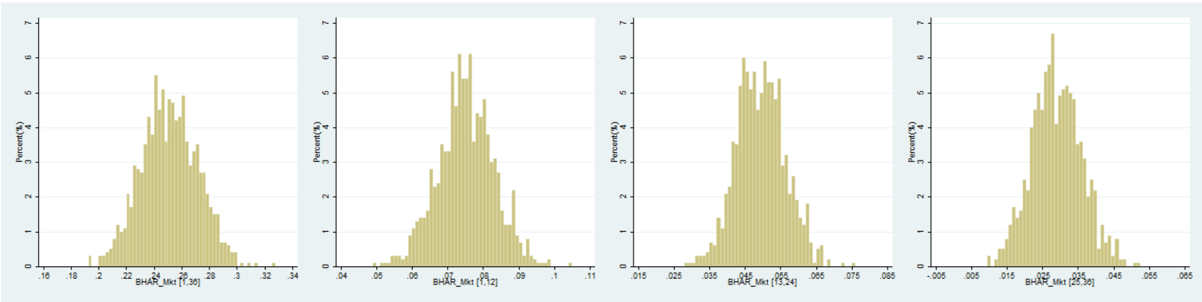
Figure 1. Market Reaction to Stock Splits Announcement

This figure plots the averaged cumulative abnormal returns for stock splits announcements in Chinese stock market in the [-10, 90] event window. Abnormal returns is based on the characteristic-adjusted returns where the stock's corresponding size and book-to-market matched portfolio return is subtracted from the raw stock return.

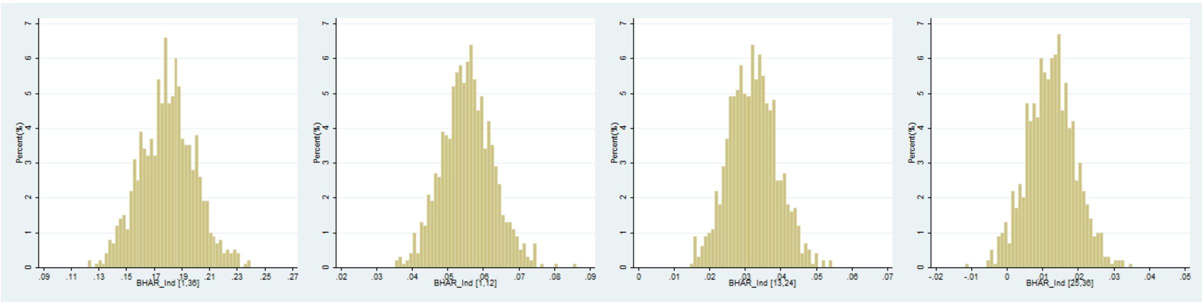
Figure 2. The Empirical Distribution of BHAR

This figure plots the empirical distribution of the mean buy-and-hold abnormal returns (BHAR) for stock splits. For each splitting stock, we randomly select a non-splitting stock in the same year-month and the same benchmark portfolio, and form a pseudo portfolio using only the non-splitting stocks and calculate the BHAR for the pseudo portfolio. We repeat the above procedure for 1,000 times and obtain the empirical distribution of the BHARs under the null of zero abnormal returns. Each event stock and its associated pseudo stock enter into the portfolio s months after the split announcement month and held for τ months. The holding periods are [1, 36], [1, 12], [12, 24] and [25, 36], respectively. We use value-weighted market portfolio as benchmark in Panel A, value-weighted industry portfolio as benchmark in Panel B, and value-weighted 25 size and book-to-market ratio independently sorted portfolio as benchmark in Panel C, and report the corresponding empirical distributions.

Panel A. BHAR with Market Portfolio as the Benchmark



Panel B. BHAR with Industry Portfolios as the Benchmark



Panel C. BHAR with 25 Size and B/M Sorted Portfolios as the Benchmark

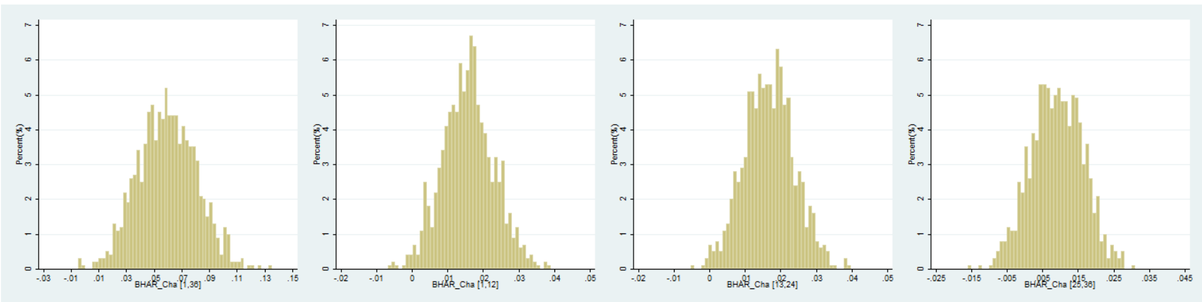
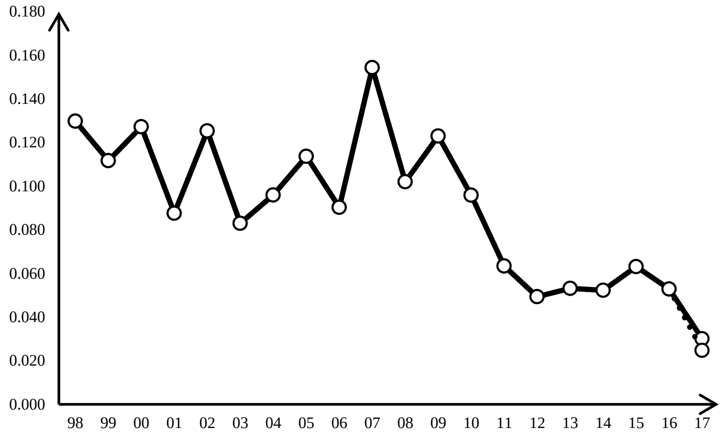


Figure 3. The Time Trend of Stock Splits

This figure plots the time trend of the mean split ratio (Panel A), the announcement effect of one unit split ratio (Panel B), and the average market reaction to stock splits (Panel C) in the Chinese A-share market from 1998 to 2017. The solid lines use all observations from Jan 1998 to Jun 2017, while the dashed line use data before Apr 8, 2017 to mitigate the effect of change in regulatory environment.

Panel A. Time Trend of the Mean Split Ratio

Panel B. Time Trend of the Announcement Effect of One Unit Stock Split Ratio



Panel C. Time Trend of the Average Market Reaction to Stock Splits

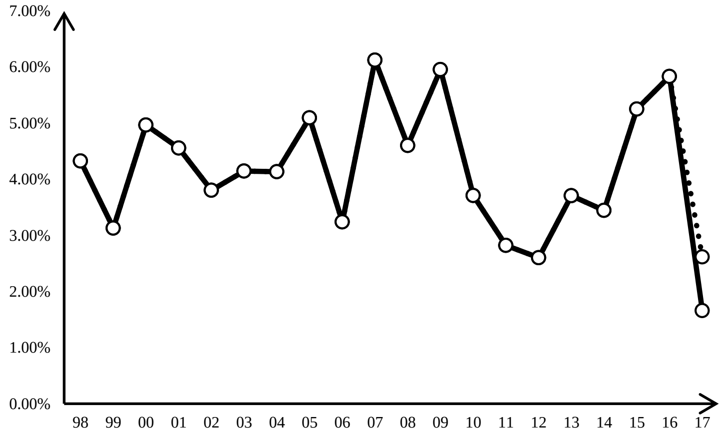


Table 1. Distribution of Stock Splits in China Year by Year

This table reports the distribution of stock splits events in Chinese A-share market each year from 1998 to 2017.

Year	# of Splitting Events	# of Splitting Firms	# of Splitting Firms	# of Splitting Events in Annual or Semi-annual Distribution Proposals						Mean Splitting Ratio	The Source of New Shares	
				Annual			Semi-Annual				% from Retained Earnings	% from Capital Surplus
				#	In Annual Report?		#	In Semi-Annual Report?				
					Yes	No		Yes	No			
1998	262	258	31.46%	206	185	21	56	51	5	0.423	48.11%	51.89%
1999	233	227	24.62%	176	110	66	57	25	32	0.466	40.91%	59.09%
2000	178	178	16.76%	131	114	17	47	41	6	0.48	29.74%	70.26%
2001	197	190	16.74%	159	152	7	38	32	6	0.466	28.18%	71.82%
2002	165	158	13.16%	134	124	10	31	31	0	0.365	22.88%	77.12%
2003	148	147	11.62%	124	118	6	24	23	1	0.461	18.50%	81.50%
2004	236	233	17.21%	196	191	5	40	38	2	0.533	16.07%	83.93%
2005	170	168	12.43%	159	157	2	11	11	0	0.452	12.01%	87.99%
2006	187	185	12.90%	153	147	6	34	34	0	0.463	16.32%	83.68%
2007	219	211	13.84%	180	173	7	39	39	0	0.47	23.42%	76.58%
2008	404	402	25.31%	371	368	3	33	32	1	0.563	20.49%	79.51%
2009	236	234	13.36%	221	219	2	15	15	0	0.489	18.76%	81.24%
2010	381	375	17.81%	341	335	6	40	35	5	0.545	21.19%	78.81%
2011	615	611	26.11%	563	543	20	52	47	5	0.658	11.77%	88.23%
2012	575	573	23.20%	542	439	103	33	22	11	0.649	6.31%	93.69%
2013	460	456	18.15%	430	317	113	30	18	12	0.659	6.93%	93.07%
2014	510	505	18.50%	465	313	152	45	13	32	0.724	6.13%	93.87%
2015	741	716	24.50%	566	380	186	175	70	105	0.947	6.19%	93.81%
2016	588	581	18.06%	532	359	173	56	24	32	1.042	4.93%	95.07%
2017	478	475	13.22%	437	312	125	41	31	10	0.768	4.45%	95.45%

Table 2. Summary Statistics

This table reports the summary statistics of the main variables used in regression analyses. The variable definitions are in Appendix A.

Variables	N	Mean	Std dev.	P25	Median	P75
CAR [-1, 1]	24383	-0.002	0.048	-0.029	-0.005	0.021
CAR [-10, 1]	24383	0.002	0.078	-0.043	-0.005	0.039
Split Dummy	24383	0.161	0.367	0	0	0
Split Ratio	24383	0.091	0.254	0	0	0
CAR [-10, -2]	24383	0.004	0.065	-0.033	-0.002	0.034
LnSize	24383	21.410	1.214	20.510	21.320	22.230
LnBM	24383	-1.106	0.661	-1.539	-1.077	-0.636
RunUp	24383	0.218	0.640	-0.202	0.029	0.437
ΔEarnings	24383	0.004	0.039	-0.006	0.001	0.010
ΔDividends	24383	0.001	0.009	-0.002	0.000	0.002
Annual Report	24383	0.971	0.169	1	1	1
ΔIlliquidity[28]	24383	0.002	0.250	-0.036	-0.002	0.025

[28] *Δ Illiquidity* is computed by multiplying the raw value with 10^8.

Table 3. The Determinants of Stock Splits

This table reports the results on the determinants of stock split decision and split ratio. The dependent variable in columns (1) to (4) is *Split Dummy*, a dummy variable equals to 1 if a firm announce stock split in this year and 0 otherwise; in columns (5) to (8) is *Split Ratio*, which is the ratio of newly issued shares from stock splits scaled by original shares outstanding. *PV_DS* is the ratio of price-to-intrinsic value following D'Mello and Shroff (2000). *PV_RRV* is the firm-specific mispricing relative to industry mean following Rhodes-Kropf, Robinson and Viswanathan (2005). *Lockup Expiration* takes value of 1 if share lockup expiration for IPOs or Split Share Structure Reform is in the t-3 to t+3 period of stock split announcement. *Share Pledge* takes value of 1 if a firm's controlling shareholder pledge its shares as collateral to raise funds. The other variables are defined in the Appendix A. The regression method used in columns (1) to (4) is the Probit model; in columns (5) to (8) is the Tobit model. T-statistics in in parentheses are based on standard errors clustered at firm level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Split Dummy				Split Ratio			
PV_DS		**-0.013*** **				**-0.009** **		
		(-2.78)				**(-2.57)**		
PV_RRV			**-0.205*** **				**-0.151*** **	
			(-4.80)				**(-4.69)**	
Lockup Expiration				**0.134*** **				**0.115*** **
				(4.16)				**(4.70)**
Share Pledge				**0.180*** **				**0.163*** **
				(6.01)				**(7.41)**
LnSize	-0.089***	-0.107***	-0.054***	-0.087***	-0.081***	-0.087***	-0.055***	-0.079***
	(-5.41)	(-5.92)	(-3.04)	(-5.28)	(-6.54)	(-7.12)	(-4.07)	(-6.43)
Runup	0.149***	0.134***	0.147***	0.146***	0.119***	0.101***	0.117***	0.116***
	(6.39)	(5.31)	(6.27)	(6.27)	(6.77)	(5.83)	(6.61)	(6.61)
LnPrice	0.597***	0.659***	0.695***	0.598***	0.499***	0.500***	0.573***	0.497***
	(17.47)	(16.83)	(17.30)	(17.46)	(19.42)	(19.01)	(18.61)	(19.44)
Δ Income	0.401	0.189	0.325	0.318	0.642***	0.451*	0.611**	0.554**
	(1.29)	(0.54)	(1.00)	(1.03)	(2.63)	(1.81)	(2.40)	(2.29)
Roe	2.421***	2.539***	2.334***	2.483***	1.675***	1.618***	1.600***	1.726***
	(12.49)	(11.30)	(11.59)	(12.80)	(11.51)	(10.60)	(10.63)	(11.94)
Age	-0.034***	-0.036***	-0.035***	-0.032***	-0.030***	-0.029***	-0.030***	-0.028***
	(-10.40)	(-9.31)	(-10.48)	(-9.61)	(-11.92)	(-10.79)	(-12.00)	(-11.02)
Capacity	0.071***	0.062***	0.052***	0.076***	0.065***	0.052***	0.051***	0.069***
	(9.05)	(6.86)	(5.95)	(9.56)	(11.03)	(8.49)	(7.71)	(11.65)
Pseudo R^2	0.165	0.172	0.166	0.168	0.164	0.177	0.165	0.168
Observations	24363	20311	24220	24363	24363	20311	24220	24363

Table 4. Short-run Market Reaction to Stock Splits

This table reports the cumulative abnormal returns (CAR) around split announcements using different event windows. We exclude observations when trading is suspend in any day during [-10, 1] window to mitigate the impact of other concurrent major corporate events. The rows correspond to different expected return models used in calculating CAR. ER is the excess return, computed by subtracting risk-free rate from the raw stock return. MKT_A is the market-adjusted abnormal return, computed by subtracting value-weighted market return from the raw stock return. IND_A is the industry-adjusted abnormal return, computed by subtracting the corresponding value-weighted industry portfolio return from the raw stock return. CHA_A is the characteristic-adjusted abnormal return, computed by subtracting the corresponding value-weighted size and book-to-market ratio matched portfolio return from the raw stock return. CAPM, FF-3 and FF-5 represent risk-adjusted abnormal returns, where we use the CAPM, Fama-French (1993) three-factor model and Fama-French (2015) five-factor model to calculate expected returns, respectively. Risk-adjusted abnormal return is computed by subtracting the model predicted expected return from the raw stock return. The parameters used in CAPM, FF-3 and FF-5 approach is estimated using the [-120, -19] pre-announcement window. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

CAR	-1	0	1	[-10,-2]	[-5,-2]	[-1,1]	[2,5]	[2,10]	[2,15]
ER	**0.007*** **	**0.010*** **	**0.002*** **	**0.030*** **	**0.017*** **	**0.018*** **	**0.003*** **	**0.007*** **	**0.013*** **
	(14.59)	**(16.34)**	**(4.32)**	**(22.62)**	**(19.13)**	**(19.41)**	**(3.64)**	**(5.56)**	**(8.14)**
MKT_A	**0.007*** **	**0.010*** **	**0.002*** **	**0.025*** **	**0.016*** **	**0.018*** **	0.000	**0.002** **	**0.007*** **
	(16.60)	**(17.71)**	**(3.73)**	**(22.88)**	**(21.86)**	**(21.10)**	(0.49)	**(2.45)**	**(5.75)**
IND_A	**0.007*** **	**0.010*** **	**0.002*** **	**0.022*** **	**0.016*** **	**0.018*** **	0.000	0.001	**0.005*** **
	(17.81)	**(18.17)**	**(3.61)**	**(21.75)**	**(22.19)**	**(21.93)**	(0.06)	(1.49)	**(4.32)**
CHA_A	**0.007*** **	**0.010*** **	**0.002*** **	**0.022*** **	**0.016*** **	**0.019*** **	0.000	0.001	**0.004*** **
	(18.87)	**(18.63)**	**(4.46)**	**(22.40)**	**(22.93)**	**(23.18)**	(0.05)	(1.00)	**(3.08)**
CAPM	**0.007*** **	**0.010*** **	**0.002*** **	**0.027*** **	**0.017*** **	**0.019*** **	**0.001* **	**0.005*** **	**0.011*** **
	(17.08)	**(18.08)**	**(4.23)**	**(23.36)**	**(22.62)**	**(21.82)**	**(1.66)**	**(4.50)**	**(8.01)**
FF-3	**0.007*** **	**0.010*** **	**0.002*** **	**0.021*** **	**0.016*** **	**0.019*** **	0.000	0.001	**0.004*** **
	(18.39)	**(18.46)**	**(4.10)**	**(19.48)**	**(21.49)**	**(22.64)**	(-0.53)	(1.26)	**(3.37)**
FF-5	**0.007*** **	**0.010*** **	**0.002*** **	**0.021*** **	**0.014*** **	**0.018*** **	0.000	0.000	0.000
	(15.00)	**(16.26)**	**(3.68)**	**(16.58)**	**(16.00)**	**(19.39)**	(0.28)	(-0.34)	(0.28)

Table 5. Long-run Stock Performance Following Stock Splits

Panel A. Buy-and-Hold Abnormal Return (BHAR) Approach

Panel A of this table reports the long-run performance of splitting stocks using the buy-and-hold abnormal return (BHAR) approach. We calculate the BHAR as the buy-and-hold cumulative returns of splitting stock minus that of a benchmark portfolio. To obtain the empirical distribution of BHAR, we randomly select a non-splitting stock in the same year-month and in the same benchmark portfolio as the splitting stock, and form a pseudo portfolio using the non-splitting stocks and calculate the BHAR for the pseudo portfolio. We repeat the above procedure for 1,000 times and obtain the empirical distribution of the BHAR under the null assumption of zero abnormal return. Each event stock and its corresponding pseudo stock are bought s months after the split announcement month and held for τ months. The holding periods are [1, 36], [1, 12], [12, 24] and [25, 36], respectively. y_h and y_l are the 95th and the 5th percentile value derived from the empirical distribution, p is the fraction of BHARs in the empirical distribution that are larger in magnitude than the BHAR of the splitting sample. The three columns MKT, IND and CHA represent different benchmark portfolios, corresponding to the value-weighted market portfolio, value-weighted industry portfolio, and value-weighted size and book-to-market ratio independently double-sorted portfolio, respectively.

Holding Period [s, s+τ]	Statistics	MKT	IND	CHA
[1,36]	BHAR	**35.51%**	**25.59%**	**11.80%**
	y_h	28.46%	21.18%	9.47%
	y_l	21.79%	14.69%	2.57%
	P	0.00	0.00	0.00
[1,12]	BHAR	**10.40%**	**7.91%**	**3.68%**
	y_h	8.84%	6.79%	2.80%
	y_l	6.20%	4.41%	0.38%
	P	0.00	0.00	0.00
[13,24]	BHAR	4.98%	2.90%	1.17%
	y_h	6.13%	4.37%	2.86%
	y_l	3.87%	2.16%	0.55%
	P	0.47	0.68	0.76
[25,36]	BHAR	**4.11%**	1.78%	1.82%
	y_h	4.06%	2.37%	2.08%
	y_l	1.73%	0.13%	-0.30%
	P	0.05	0.21	0.10

Panel B. Calendar-Time Portfolio Approach

Panel B of this table reports the long-run performance of splitting stocks using the calendar-time portfolio approach. In each month, we select all the stocks announcing split in the previous [1, 36] months, [1, 12] months, [13, 24] months or [25, 36] months according to the required holding period and form portfolios. Column (1) report the time-series average excess return. Columns (2) to (6) report alphas estimated from the time-series regression of excess returns on market factor, the Fama and French (1993) three factors, the Carhart (1997) four factors, the Fama and French (2015) five factors and the Liu, Stambaugh and Yuan (2018) three factors, respectively. The upper part of Panel B reports the results for equal-weighted portfolio and the bottom part reports the results for value-weighted portfolio. The number reported in parentheses are t statistics, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Holding Period [s, s+τ]	ER	CAPM	FF-3	Carhart-4	FF-5	CH-3
Equal Weighted Stock Split Portfolio						
[1, 36]	**0.015****	**0.006****	0.002	0.001	0.000	0.002
	(2.28)	**(2.54)**	(1.39)	(1.09)	(0.34)	(1.60)
[1, 12]	**0.015****	**0.007****	**0.003***	0.002	0.001	0.002
	(2.34)	**(2.55)**	**(1.88)**	(1.55)	(0.64)	(1.01)
[13, 24]	**0.014****	**0.006****	0.001	0.001	-0.000	0.002
	(2.22)	**(2.32)**	(1.00)	(0.64)	(-0.03)	(1.17)
[25, 36]	**0.015****	**0.006****	0.001	0.001	0.001	**0.003****
	(2.28)	**(2.55)**	(1.30)	(1.12)	(1.03)	**(2.41)**
Value Weighted Stock Split Portfolio						
[1, 36]	**0.010***	0.002	0.001	0.001	0.000	0.001
	(1.66)	(1.21)	(1.17)	(0.65)	(0.32)	(0.41)
[1, 12]	**0.011***	0.003	**0.003****	0.002	0.002	0.001
	(1.80)	(1.49)	**(2.25)**	(1.55)	(1.03)	(0.54)
[13, 24]	0.009	0.001	0.000	-0.000	-0.001	-0.001
	(1.51)	(0.53)	(0.28)	(-0.39)	(-0.51)	(-0.35)
[25, 36]	**0.010***	0.002	0.002	0.001	0.002	0.001
	(1.66)	(1.12)	(1.41)	(1.01)	(1.22)	(0.86)

Table 6. Regression Analyses

Panel A and B of this table reports the regression analyses of short-run market reaction to stock splits. The dependent variable (*CAR[-1, 1]*, (*CAR[-10, 1]*) are cumulative abnormal returns over the event window of [-1, 1] and [-10, 1], respectively. In Panel A, the key explanatory variable, *Split Dummy,* equals to 1 if a firm conducts stock splits and 0 otherwise. In Panel B, the key explanatory variable, *Split Ratio,* is the ratio of newly issued shares from stock splits as a fraction of the original number of shares outstanding. Other variables are defined in the Appendix A. The regression method used in Columns (1) to (4) is OLS with event date and firm fixed effects (standard errors clustered by event date). Columns (5) and (6) use the Fama-Macbeth regression, where we run cross-sectional regression with industry fixed effects year by year and report the time-series average of regression coefficients. The sample used in Columns (3) and (4) is a propensity-scored matched sample. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Short-run Market Reaction to Stock Splits

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		PSM		Fama-Macbeth	
CAR	[-1,1]	[-10,1]	[-1,1]	[-10,1]	[-1,1]	[-10,1]
Split Dummy	**0.025*****	**0.040*****	**0.025*****	**0.041*****	**0.024*****	**0.042*****
	(21.62)	**(22.47)**	**(13.69)**	**(14.76)**	**(16.25)**	**(16.55)**
CAR[-10,-2]	-0.080***		-0.086***		-0.083***	
	(-10.77)		(-6.28)		(-11.55)	
LnSize	-0.003***	-0.008***	-0.002	-0.008***	0.000	-0.001
	(-4.36)	(-6.14)	(-0.94)	(-2.92)	(0.46)	(-0.30)
LnBM	0.000	0.001	0.004**	0.003	0.001	0.003*
	(0.27)	(0.63)	(2.02)	(0.84)	(1.28)	(1.86)
RunUp	-0.005***	-0.003	-0.006***	-0.005	-0.005**	0.001
	(-4.92)	(-1.46)	(-3.08)	(-1.57)	(-2.65)	(0.17)
ΔEarnings	-0.010	0.070***	0.007	0.098*	0.032	0.134***
	(-1.04)	(4.45)	(0.21)	(1.91)	(1.21)	(4.37)
ΔDividends	0.142***	0.279***	0.040	0.235*	0.188***	0.310***
	(4.05)	(4.90)	(0.48)	(1.81)	(4.36)	(4.57)
Annual Report	-0.012***	-0.015***	-0.016***	-0.020***	-0.010*	-0.011*
	(-4.07)	(-2.98)	(-3.42)	(-2.60)	(-1.89)	(-2.01)
ΔIlliquidity	-1.268***	-2.594***	-1.979***	-3.967***	-2.691***	-5.165***
	(-7.24)	(-8.34)	(-3.92)	(-4.62)	(-4.78)	(-4.91)
Event Date Effect	Yes	Yes	Yes	Yes		
Firm Effect	Yes	Yes	Yes	Yes		
Industry Effect					Yes	Yes
R^2/Avg R^2	0.095	0.089	0.148	0.140	0.094	0.112
Observations	23992	23992	6994	6994	24383	24383

Panel B. Short-run Market Reaction to Stock Splits Ratio

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		PSM		Fama-Macbeth	
CAR	[-1,1]	[-10,1]	[-1,1]	[-10,1]	[-1,1]	[-10,1]
Split Ratio	**0.043*****	**0.071*****	**0.042*****	**0.070*****	**0.046*****	**0.091*****
	(20.80)	**(23.42)**	**(15.17)**	**(16.79)**	**(12.00)**	**(12.03)**
CAR[-10,-2]	-0.085***		-0.096***		-0.090***	
	(-11.27)		(-7.09)		(-11.77)	
LnSize	-0.003***	-0.007***	-0.001	-0.008***	0.001	-0.000
	(-4.18)	(-5.92)	(-0.79)	(-2.74)	(0.69)	(-0.21)
LnBM	0.000	0.001	0.005**	0.004	0.002	0.004**
	(0.56)	(0.92)	(2.40)	(1.20)	(1.56)	(2.24)
RunUp	-0.006***	-0.004*	-0.008***	-0.007**	-0.006**	-0.002
	(-5.30)	(-1.96)	(-3.74)	(-2.25)	(-2.83)	(-0.44)
ΔEarnings	-0.009	0.070***	-0.001	0.083*	0.035	0.136***
	(-0.94)	(4.46)	(-0.04)	(1.66)	(1.27)	(4.18)
ΔDividends	0.136***	0.269***	0.041	0.233*	0.184***	0.306***
	(3.88)	(4.77)	(0.50)	(1.82)	(4.26)	(4.62)
Annual Report	-0.005*	-0.003	-0.007	-0.005	-0.007	-0.006
	(-1.84)	(-0.59)	(-1.49)	(-0.58)	(-1.46)	(-1.15)
ΔIlliquidity	-1.226***	-2.502***	-1.898***	-3.782***	-2.557***	-4.786***
	(-6.92)	(-7.99)	(-3.76)	(-4.39)	(-4.85)	(-5.04)
Event Date Effect	Yes	Yes	Yes	Yes		
Firm Effect	Yes	Yes	Yes	Yes		
Industry Effect					Yes	Yes
R^2/Avg R^2	0.102	0.099	0.168	0.164	0.099	0.130
Observations	23992	23992	6994	6994	24383	24383

Panel C. Long-run Stock Performance Following Stock Splits

Panel C of this table reports the regression results of long-run stock performance following splits. The dependent variable is monthly stock return. *Split Dummy [1, 36]* equals to 1 if a firm conducts stock split in the past 36 months and 0 otherwise. We further decompose *Split Dummy* into 3 dummy variables based on whether a firm conducts stock split in the past 1 to 12, 12 to 24, and 25 to 36 months. *Split Ratio [1, 36]* is the ratio of newly issued shares from stock splits as a fraction of original number of shares in the past 36 months, and the associated 3 variables are the corresponding *Split Ratio* if stock split is in the past 1 to 12, 12 to 24 and 25 to 36 months. If stock split occurs multiple times during the window, the latest stock split is used to define *Split Ratio*. The regression method is Fama-Macbeth regression, where we run cross-sectional regression with industry fixed effects year by year and report the time-series average of regression coefficients. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)		(3)	(4)
Split Dummy [1, 36]	**0.006*** **		Split Ratio [1, 36]	**0.009*** **	
	(4.29)			**(3.74)**	
Split Dummy [1, 12]		**0.006*** **	Split Ratio [1, 12]		**0.009*** **
		(4.30)			**(3.76)**
Split Dummy [13, 24]		-0.001	Split Ratio [13, 24]		-0.013
		(-0.22)			(-1.21)
Split Dummy [25, 36]		0.003	Split Ratio [25, 36]		0.006
		(1.59)			(1.25)
LnSize	-0.006***	-0.006***	LnSize	-0.006***	-0.006***
	(-4.50)	(-4.49)		(-4.50)	(-4.49)
LnBM	0.002**	0.002**	LnBM	0.002**	0.002**
	(2.07)	(2.07)		(2.14)	(2.12)
Ret(-1, 0)	-0.063***	-0.063***	Ret(-1 0)	-0.063***	-0.063***
	(-9.30)	(-9.32)		(-9.23)	(-9.25)
Ret(-12, -1)	-0.003	-0.003	Ret(-12 -1)	-0.003	-0.003
	(-0.89)	(-0.91)		(-0.93)	(-0.94)
Asset Growth	-0.002**	-0.002**	Asset Growth	-0.002**	-0.002**
	(-2.25)	(-2.24)		(-2.30)	(-2.27)
ROA	0.001	0.001	ROA	0.002	0.002
	(0.12)	(0.11)		(0.16)	(0.16)
Industry Effect	Yes	Yes	Industry Effect	Yes	Yes
Ave R^2	0.139	0.140	Ave R^2	0.140	0.141
Observations	314534	314534	Observations	314534	314534

Table 7. Fundamentals of Splitting Firms

This table report the fundamental performance of splitting firms in the year of and two years after split. The dependent variable used in Panel A is ROA, defined as the operating income deflated by total assets. The dependent variable in Panel B is earnings growth relative to the earnings in year t-1, in Panel C is sales growth rate relative to the sales in year t-1, and in Panel D is earnings surprise. *Split Dummy* is a dummy variable equals to 1 if a firm conducts stock splits and 0 otherwise. *Split Ratio* is newly issued shares from stock splits as a fraction of original number of shares outstanding. The other variables are defined in the Appendix A. The regression method used is OLS with industry and year fixed effects. T-statistics in parentheses are based on standard errors clustered at firm level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Stock split and ROA

	(1)	(2)	(3)		(4)	(5)	(6)
	ROA_t	ROA_{t+1}	ROA_{t+2}		ROA_t	ROA_{t+1}	ROA_{t+2}
Split Dummy	**0.015*** **	**0.017*** **	**0.015*** **	Split Ratio	**0.019*** **	**0.021*** **	**0.020*** **
	(23.46)	**(15.05)**	**(8.65)**		**(19.68)**	**(13.05)**	**(7.63)**
LnSize	0.007***	0.007***	0.006***	LnSize	0.007***	0.008***	0.006***
	(20.29)	(12.78)	(5.77)		(20.41)	(12.87)	(5.86)
LnBM	-0.012***	-0.016***	-0.021***	LnBM	-0.012***	-0.016***	-0.021***
	(-18.27)	(-14.51)	(-12.67)		(-18.20)	(-14.45)	(-12.61)
Runup	0.017***	0.030***	0.029***	Runup	0.018***	0.031***	0.029***
	(26.69)	(26.17)	(18.31)		(26.87)	(26.31)	(18.34)
ROA_{t-1}	0.703***	0.720***	0.729***	ROA_{t-1}	0.708***	0.725***	0.732***
	(60.74)	(45.52)	(31.91)		(61.24)	(45.59)	(31.83)
Industry Effect	Yes	Yes	Yes	Industry Effect	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Year Effect	Yes	Yes	Yes
Adj-R^2	0.498	0.355	0.237	Adj-R^2	0.495	0.353	0.237
N	23154	23105	21063	N	23154	23105	21063

Panel B. Stock split and earnings growth

	(1)	(2)	(3)		(4)	(5)	(6)
	$\Delta Earnings_t$	$\Delta Earnings_{t+1}$	$\Delta Earnings_{t+2}$		$\Delta Earnings_t$	$\Delta Earnings_{t+1}$	$\Delta Earnings_{t+2}$
Split Dummy	**0.009*** **	**0.009*** **	**0.007*** **	Split Ratio	**0.010*** **	**0.011*** **	**0.009*** **
	(21.31)	**(12.59)**	**(6.69)**		**(17.63)**	**(11.64)**	**(6.21)**
LnSize	0.004***	0.004***	0.004***	LnSize	0.004***	0.004***	0.004***
	(14.98)	(9.63)	(5.35)		(15.02)	(9.67)	(5.37)
LnBM	-0.006***	-0.005***	-0.003***	LnBM	-0.006***	-0.005***	-0.003***
	(-14.68)	(-7.22)	(-3.54)		(-14.68)	(-7.23)	(-3.56)
Runup	0.011***	0.017***	0.016***	Runup	0.011***	0.017***	0.016***
	(24.74)	(25.14)	(18.30)		(25.16)	(25.41)	(18.38)
ROA_{t-1}	-0.164***	-0.177***	-0.186***	ROA_{t-1}	-0.161***	-0.174***	-0.183***
	(-26.83)	(-22.12)	(-16.87)		(-26.37)	(-21.70)	(-16.63)
Industry Effect	Yes	Yes	Yes	Industry Effect	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Year Effect	Yes	Yes	Yes
Adj-R^2	0.129	0.107	0.071	Adj-R^2	0.126	0.105	0.071
N	23154	23105	21063	N	23154	23105	21063

Panel C. Stock split and sales growth

	(1)	(2)	(3)		(4)	(5)	(6)
	$\Delta Sales_t$	$\Delta Sales_{t+1}$	$\Delta Sales_{t+2}$		$\Delta Sales_t$	$\Delta Sales_{t+1}$	$\Delta Sales_{t+2}$
Split Dummy	**0.113*** **	**0.196*** **	**0.272*** **	Split Ratio	**0.164*** **	**0.296*** **	**0.432*** **
	(12.33)	**(10.06)**	**(8.54)**		**(11.44)**	**(10.06)**	**(8.78)**
LnSize	0.033***	0.032***	-0.006	LnSize	0.034***	0.034***	-0.003
	(9.66)	(4.01)	(-0.39)		(9.95)	(4.26)	(-0.17)
LnBM	-0.138***	-0.301***	-0.470***	LnBM	-0.137***	-0.299***	-0.468***
	(-15.69)	(-14.24)	(-12.52)		(-15.61)	(-14.19)	(-12.51)
Runup	0.110***	0.299***	0.386***	Runup	0.109***	0.297***	0.381***
	(13.15)	(15.17)	(12.39)		(13.07)	(15.16)	(12.30)
ROA_{t-1}	-1.134***	-2.248***	-2.872***	ROA_{t-1}	-1.113***	-2.219***	-2.841***
	(-11.92)	(-10.86)	(-8.17)		(-11.76)	(-10.76)	(-8.09)
Industry Effect	Yes	Yes	Yes	Industry Effect	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Year Effect	Yes	Yes	Yes
Adj-R^2	0.067	0.074	0.063	Adj-R^2	0.067	0.074	0.063
N	23142	23092	21042	N	23142	23092	21042

Panel D. Stock split and earnings surprise

	(1)	(2)	(3)		(4)	(5)	(6)
	$Suprise_t$	$Suprise_{t+1}$	$Suprise_{t+2}$		$Suprise_t$	$Suprise_{t+1}$	$Suprise_{t+2}$
Split Dummy	**0.002*** **	**0.001***	**0.001** **	Split Ratio	**0.002*** **	**0.001**	**0.001** **
	(7.17)	**(1.72)**	**(1.97)**		**(8.37)**	**(1.30)**	**(2.22)**
LnSize	-0.000***	-0.000**	-0.000	LnSize	-0.000***	-0.000***	-0.000
	(-3.44)	(-2.56)	(-1.61)		(-3.41)	(-2.59)	(-1.58)
LnBM	-0.002***	-0.002***	-0.002***	LnBM	-0.002***	-0.002***	-0.002***
	(-5.72)	(-5.39)	(-2.69)		(-5.82)	(-5.44)	(-2.69)
Runup	0.001***	0.001*	0.000	Runup	0.001***	0.001**	0.000
	(5.19)	(1.91)	(1.03)		(5.26)	(1.97)	(0.99)
ROA_{t-1}	0.004	0.016***	0.040***	ROA_{t-1}	0.005	0.016***	0.040***
	(1.31)	(3.73)	(5.19)		(1.46)	(3.80)	(5.19)
Industry Effect	Yes	Yes	Yes	Industry Effect	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Year Effect	Yes	Yes	Yes
Adj-R^2	0.076	0.025	0.040	Adj-R^2	0.075	0.025	0.040
N	8245	7432	6863	N	8245	7432	6863

Table 8. Stock Splits and Expectations of Future Performance

This table reports the effect of stock splits on analysts' expectation about firms' future performance. The dependent variable *Update* is the revision of analyst consensus forecast of the earnings before and after the split announcement. We use the forecast of earnings in fiscal year t+1 in columns (1) to (5), forecast of earnings in year t+2 in column (6), and the sum of forecast of earnings in year t+1 and year t+2 in column (7). *Split Dummy* is a dummy variable equals 1 if a firm conducts stock splits and 0 otherwise. *Split Ratio* is the newly issued shares from stock splits as a fraction of original number of shares outstanding. Other variables are defined in Appendix A. The regression method used in columns (1), (2), (4), (6) and (7) is OLS with firm and year fixed effects with standard errors clustered at firm level. In column (3), we use the Heckman two-stage procedure to correct the selection bias. In column (5), we use the Fama-Macbeth regression. The sample used in column (4) is a propensity-score matched sample. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			$Update_{y+1}$			$Update_{y+2}$	$Update_{[y+1, y+2]}$
	OLS		Heckman	PSM	Fama-Macbeth	OLS	
Split Dummy	**0.003*** **						
	(3.49)						
Split Ratio		**0.004*** **	**0.004*** **	**0.003** **	**0.006*** **	**0.003*** **	**0.007*** **
		(3.61)	**(5.71)**	**(2.17)**	**(4.46)**	**(2.65)**	**(3.22)**
LnCoverage	-0.003***	-0.003***	0.000	-0.002	0.000	-0.005***	-0.009***
	(-4.00)	(-4.01)	(0.39)	(-0.84)	(0.55)	(-4.69)	(-4.46)
LnSize	-0.008***	-0.008***	-0.001**	-0.007***	-0.000	-0.010***	-0.017***
	(-9.61)	(-9.66)	(-2.06)	(-5.29)	(-0.78)	(-10.15)	(-9.77)
LnBM	-0.003**	-0.003**	0.001	0.000	0.001	-0.002	-0.005*
	(-2.50)	(-2.49)	(1.28)	(0.04)	(0.69)	(-1.27)	(-1.77)
ΔEarnings	0.086***	0.086***	0.115***	0.187***	0.130***	0.092***	0.171***
	(4.73)	(4.75)	(7.46)	(3.31)	(6.60)	(4.28)	(4.48)
ΔDividends	0.217***	0.214***	0.224***	0.130*	0.206***	0.208***	0.435***
	(4.94)	(4.88)	(5.92)	(1.76)	(4.74)	(3.82)	(4.54)
Earnings Volatility	0.022	0.021	-0.032	-0.130	-0.047	-0.034	-0.013
	(0.60)	(0.58)	(-1.32)	(-1.16)	(-1.06)	(-0.82)	(-0.18)
Year Effect	Yes	Yes	Yes	Yes		Yes	Yes
Firm Effect	Yes	Yes		Yes		Yes	Yes
Industry Effect			Yes		Yes		
R^2/Ave R^2	0.070	0.070		0.163		0.105	0.095
Observations	11350	11350	17798	4715	11350	10911	10872

Table 9. Stock Splits, Underperformance and Long-run Stock Returns

This table reports the long-run return performance of splitting and non-splitting stocks 3 years after split. The dependent variable *BHAR[1, 36]* is 36-months buy-and-hold abnormal returns relative to a benchmark portfolio. Columns MKT, IND and CHA use the value-weighted market, 22 industry and 25 size and book-to-market ratio double-sorted portfolios as the benchmark, respectively. *Split Dummy* equals 1 if a firm conducts stock splits and 0 otherwise. *Split Ratio* is the newly issued shares from stock splits scaled by original number of shares outstanding. In columns (1) to (6), *Underperform* is a dummy variable equals 1 if realized earnings in any of the three post-split years is below the earnings in the year of splits. In columns (7) to (12), *Underperform* is a dummy variable equals 1 if ROA in any of the three post-split years is below the industry average ROA. Other variables are defined in the Appendix A. The regression method is Fama-Macbeth regression. T-statistics in parentheses are Newey-West adjusted (lag=3). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BHAR [1, 36]	MKT		IND		CHA		MKT		IND		CHA	
	Below Prior Year						Below Industry Average					
Split Dummy	0.099		0.104		0.102		0.076		0.077		0.079	
	(1.53)		(1.61)		(1.57)		(1.34)		(1.38)		(1.33)	
Split Ratio		0.124		0.134		0.134		0.083		0.085		0.087
		(1.06)		(1.12)		(1.08)		(0.89)		(0.91)		(0.83)
Split Dummy × Underperform	**-0.157****		**-0.163****		**-0.153****		**-0.133****		**-0.133****		**-0.129****	
	(-2.22)		**(-2.26)**		**(-2.18)**		**(-2.46)**		**(-2.48)**		**(-2.28)**	
Split Ratio × Underperform		**-0.268****		**-0.280****		**-0.268****		**-0.218****		**-0.218****		**-0.211****
		(-2.27)		**(-2.25)**		**(-2.21)**		**(-2.69)**		**(-2.66)**		**(-2.29)**
Underperform	-0.222***	-0.224***	-0.221***	-0.223***	-0.223***	-0.225***	-0.099**	-0.106***	-0.100**	-0.107***	-0.101**	-0.109***
	(-5.11)	(-4.99)	(-5.13)	(-5.04)	(-4.63)	(-4.54)	(-2.63)	(-3.02)	(-2.66)	(-3.06)	(-2.91)	(-3.36)
LnSize	-0.243***	-0.244***	-0.242***	-0.243***	-0.058***	-0.059***	-0.257***	-0.258***	-0.256***	-0.256***	-0.072***	-0.073***
	(-3.73)	(-3.75)	(-3.71)	(-3.73)	(-4.94)	(-5.04)	(-4.02)	(-4.04)	(-4.00)	(-4.02)	(-6.36)	(-6.46)
LnBM	0.234***	0.232***	0.234***	0.232***	0.123***	0.122***	0.255***	0.253***	0.255***	0.253***	0.145***	0.143***
	(4.21)	(4.18)	(4.20)	(4.17)	(3.49)	(3.47)	(4.43)	(4.41)	(4.42)	(4.40)	(3.97)	(3.96)
RunUp	-0.429***	-0.423***	-0.430***	-0.424***	-0.419***	-0.413***	-0.446***	-0.441***	-0.446***	-0.442***	-0.437***	-0.432***
	(-3.81)	(-3.79)	(-3.82)	(-3.80)	(-3.78)	(-3.76)	(-3.93)	(-3.93)	(-3.95)	(-3.93)	(-3.89)	(-3.87)
3 Year Asset Growth	0.101***	0.101***	0.101***	0.100***	0.098***	0.098***	0.104***	0.104***	0.104***	0.103***	0.101***	0.101***

	(5.45)	(5.42)	(5.52)	(5.50)	(5.48)	(5.47)	(5.43)	(5.35)	(5.50)	(5.42)	(5.44)	(5.39)
3 Year Ave ROA	1.542***	1.550***	1.542***	1.550***	1.474***	1.482***	1.663***	1.668***	1.662***	1.667***	1.595***	1.600***
	(3.37)	(3.38)	(3.38)	(3.39)	(3.30)	(3.31)	(3.03)	(3.04)	(3.04)	(3.04)	(2.96)	(2.97)
Industry Effect	√	√	√	√	√	√	√	√	√	√	√	√
Ave R^2	0.319	0.319	0.279	0.279	0.260	0.261	0.311	0.311	0.271	0.271	0.252	0.253
Observations	18677	18677	18677	18677	18677	18677	18677	18677	18677	18677	18677	18677

Table 10. Cross-sectional Heterogeneity

Panel A: OLS Regression

This table reports the results of short-run market reaction to stock splits conditional on certain firm characteristics. The dependent variable (*CAR[-1, 1]*, (*CAR[-10, 1]*) are cumulative abnormal returns over the event window [-1, 1] and [-10, 1], respectively. *Split Ratio* is the newly issued shares from stock splits scaled by original number of shares outstanding. The interaction variable *Z* used in columns (1) and (2) is *LnSize*, defined as the natural logarithm of firm market capitalization. In columns (3) and (4), the interaction variable is *LnCoverage*, defined as the natural logarithm of one plus the number of analysts following the firm. In columns (5) and (6), the interaction variable is *Institutional Holdings*, the proportion of shares held by institutional investors. Other variables are defined in the Appendix A. The regression method used in Panel A and B is OLS with event date and firm fixed effects (standard errors clustered by event date). The method used in Panel C is Fama-Macbeth regression. Panel A and C use the full sample, while Panel B uses the propensity score matched sample. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Interaction variable Z	LnSize		LnCoverage		Institutional Ownership	
CAR	[-1,1]	[-10,1]	[-1,1]	[-10,1]	[-1,1]	[-10,1]
Split Ratio	0.157***	0.345***	0.058***	0.095***	0.054***	0.082***
	(5.12)	(7.49)	(12.89)	(15.30)	(18.11)	(19.66)
Split Ratio ×Z	**-0.005*****	**-0.013*****	**-0.008*****	**-0.013*****	**-0.001*****	**-0.001*****
	(-3.76)	**(-6.01)**	**(-4.54)**	**(-5.48)**	**(-7.99)**	**(-5.50)**
CAR[-10,-2]	-0.085***		-0.086***		-0.085***	
	(-11.37)		(-10.72)		(-10.72)	
Z			-0.002***	-0.002***	0.000***	-0.000
			(-3.13)	(-2.73)	(3.11)	(-1.35)
LnSize	-0.002***	-0.006***	-0.003***	-0.008***	-0.004***	-0.008***
	(-3.20)	(-4.61)	(-3.41)	(-5.25)	(-4.51)	(-5.78)
LnBM	0.000	0.001	-0.001	-0.001	-0.001	-0.002
	(0.42)	(0.73)	(-0.94)	(-0.47)	(-0.69)	(-1.04)
RunUp	-0.006***	-0.004**	-0.005***	-0.003	-0.005***	-0.002
	(-5.44)	(-2.17)	(-4.47)	(-1.62)	(-4.24)	(-0.84)
ΔEarnings	-0.009	0.070***	-0.030***	0.044***	-0.031***	0.044***
	(-0.92)	(4.48)	(-3.13)	(2.79)	(-3.23)	(2.79)
ΔDividends	0.142***	0.282***	0.152***	0.319***	0.137***	0.292***
	(4.04)	(5.01)	(3.81)	(4.90)	(3.36)	(4.45)
Annual Report	-0.005*	-0.003	-0.012***	-0.006	-0.010**	-0.003
	(-1.83)	(-0.58)	(-2.90)	(-0.76)	(-2.52)	(-0.38)
ΔIlliquidity	-1.227***	-2.501***	-1.066***	-2.136***	-0.012***	-0.024***
	(-6.92)	(-7.99)	(-5.29)	(-5.46)	(-5.97)	(-6.18)
Event Date Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.103	0.101	0.107	0.101	0.111	0.102
Observations	23992	23992	20466	20466	20122	20122

Panel B: Propensity Score Matched Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Interaction Z	LnSize		LnCoverage		Institutional Ownership	
CAR	[-1,1]	[-10,1]	[-1,1]	[-10,1]	[-1,1]	[-10,1]
Split Ratio	0.175***	0.379***	0.064***	0.095***	0.054***	0.081***
	(3.97)	(5.92)	(9.69)	(9.72)	(13.41)	(12.95)
Split Ratio ×Z	**-0.006*****	**-0.014*****	**-0.010*****	**-0.013*****	**-0.059*****	**-0.075*****
	(-3.04)	**(-4.86)**	**(-4.09)**	**(-3.64)**	**(-4.99)**	**(-3.93)**
CAR[-10,-2]	-0.098***		-0.097***		-0.097***	
	(-7.22)		(-6.43)		(-6.47)	
Z			-0.001	-0.000	0.015**	0.009
			(-0.56)	(-0.18)	(2.08)	(0.80)
LnSize	0.001	-0.003	0.000	-0.006*	-0.000	-0.007**
	(0.28)	(-1.13)	(0.18)	(-1.94)	(-0.11)	(-2.08)
LnBM	0.005**	0.004	0.004	0.003	0.005*	0.003
	(2.37)	(1.16)	(1.57)	(0.68)	(1.78)	(0.75)
Run Up	-0.008***	-0.008**	-0.007***	-0.007**	-0.007***	-0.007*
	(-3.80)	(-2.34)	(-3.26)	(-1.99)	(-3.21)	(-1.89)
ΔEarnings	-0.001	0.084*	-0.030	0.039	-0.025	0.047
	(-0.02)	(1.68)	(-0.88)	(0.73)	(-0.75)	(0.87)
ΔDividends	0.049	0.251**	0.056	0.322**	0.050	0.312**
	(0.60)	(1.97)	(0.60)	(2.20)	(0.54)	(2.14)
Annual Report	-0.007	-0.006	-0.009	-0.011	-0.008	-0.010
	(-1.58)	(-0.70)	(-1.54)	(-1.05)	(-1.43)	(-0.96)
ΔIlliquidity	-1.872***	-3.712***	-2.365***	-4.381***	-2.544***	-4.631***
	(-3.72)	(-4.34)	(-3.85)	(-3.87)	(-4.11)	(-4.08)
Event Date Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.170	0.169	0.181	0.169	0.179	0.167
Observations	6994	6994	5840	5840	5837	5837

Panel C: Fama-Macbeth Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Interaction Z	LnSize		LnCoverage		Institutional Holdings	
CAR	[-1,1]	[-10,1]	[-1,1]	[-10,1]	[-1,1]	[-10,1]
Split Ratio	0.145*	0.262*	0.064***	0.112***	0.059***	0.107***
	(1.87)	(2.06)	(8.79)	(9.58)	(8.58)	(8.38)
Split Ratio ×Z	-0.004	-0.008	**-0.011******	**-0.015******	**-0.001******	**-0.001******
	(-1.20)	(-1.28)	**(-3.59)**	**(-3.60)**	**(-5.61)**	**(-5.91)**
CAR[-10,-2]	-0.091***		-0.091***		-0.093***	
	(-11.94)		(-9.83)		(-9.95)	
Z			-0.001	-0.001	0.000	-0.000
			(-1.29)	(-0.72)	(1.31)	(-0.18)
LnSize	0.001	0.000	0.002*	0.001	0.002	0.001
	(1.18)	(0.25)	(2.01)	(0.30)	(1.64)	(0.33)
LnBM	0.002	0.004**	-0.001	0.001	-0.001	-0.001
	(1.39)	(2.11)	(-1.22)	(0.52)	(-1.70)	(-0.57)
RunUp	-0.006**	-0.002	-0.004**	0.001	-0.003**	0.002
	(-2.72)	(-0.38)	(-2.25)	(0.30)	(-2.32)	(0.60)
ΔEarnings	0.035	0.137***	-0.020	0.081**	-0.022*	0.079**
	(1.28)	(4.12)	(-1.71)	(2.80)	(-1.85)	(2.84)
ΔDividends	0.187***	0.307***	0.201***	0.338***	0.187***	0.332***
	(4.28)	(4.53)	(4.29)	(4.79)	(3.84)	(4.64)
Annual Report	-0.007	-0.005	-0.008	-0.007	-0.010	-0.011
	(-1.39)	(-0.97)	(-1.48)	(-1.00)	(-1.71)	(-1.59)
ΔIlliquidity	-2.492***	-4.698***	-2.761***	-5.072***	-0.029***	-0.053***
	(-4.82)	(-4.96)	(-4.11)	(-4.11)	(-4.10)	(-4.10)
Industry Effect	Yes	Yes	Yes	Yes	Yes	Yes
Ave R^2	0.102	0.133	0.101	0.126	0.104	0.130
Observations	24383	24383	20833	20833	20478	20478

Table 11. Controlling for Other Potential Channels

This table reports the results after taking into account of other channels. The dependent variable *CAR[-1, 1]* is the cumulative abnormal returns over the window [-1, 1]. *Split Ratio* is the ratio of newly issued shares from stock splits scaled by original number of shares outstanding. In columns (1) and (4), only shares issued using capital surplus are used in the sample. *Retained Earnings* is the ratio of newly issued shares generated from retained earnings scaled by original number of shares outstanding. *ΔCoverage* and *ΔShareholder* are the change of analyst coverage and total number of shareholders around stock splits, respectively. *ΔTurnover* and *ΔVolatility* are the change of stock turnover ratio and return volatility around stock splits. Other variables are defined in the Appendix A. The regression method is OLS with event date and firm fixed effects and standard errors are clustered by event date. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Split Ratio	**0.042*** **	**0.042*** **	**0.041*** **	**0.041*** **
	(18.69)	**(18.33)**	**(17.83)**	**(16.35)**
CAR[-10,-2]	-0.085***	-0.088***	-0.090***	-0.090***
	(-11.28)	(-10.82)	(-11.03)	(-11.03)
LnSize	-0.003***	-0.003***	-0.003***	-0.003***
	(-4.19)	(-3.39)	(-3.33)	(-3.33)
LnBM	0.000	-0.000	-0.000	-0.000
	(0.58)	(-0.45)	(-0.47)	(-0.46)
Run Up	-0.006***	-0.006***	-0.005***	-0.005***
	(-5.34)	(-4.95)	(-4.23)	(-4.24)
ΔEarnings	-0.009	-0.030***	-0.032***	-0.032***
	(-0.95)	(-3.16)	(-3.31)	(-3.32)
ΔDividends	0.137***	0.139***	0.141***	0.141***
	(3.89)	(3.40)	(3.44)	(3.45)
Annual Report	-0.006*	-0.010**	-0.010**	-0.010**
	(-1.87)	(-2.46)	(-2.44)	(-2.46)
ΔIlliquidity	-0.012***	-0.013***	-0.011***	-0.011***
	(-6.93)	(-5.32)	(-4.31)	(-4.31)
Retained Earnings	0.047***			0.044***
	(9.30)			(7.63)
ΔCoverage		1.317***	1.273***	1.274***
		(4.71)	(4.56)	(4.57)
ΔShareholder		-0.804***	-0.746***	-0.747***
		(-3.41)	(-3.14)	(-3.15)
ΔTurnover			0.000***	0.000***
			(4.46)	(4.46)
ΔVolatility			-0.047	-0.048
			(-0.75)	(-0.75)
Event Date Effect	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes
R^2	0.102	0.108	0.110	0.110
Observations	23992	19478	19477	19477

Table 12. Announcement effects of stock splits conditional on pre-split share prices

This table reports the announcement effects of stock splits conditional on pre-split share prices. The dependent variable (*CAR[-1, 1]*, (*CAR[-10, 1]*) are cumulative abnormal returns over the event window [-1, 1] and [-10, 1], respectively. *Split Ratio* is the ratio of newly issued shares from stock splits scaled by original number of shares outstanding. *LnPrice* is the natural logarithm of stock price 11 days before announcement. Other variables are defined in the Appendix A. The regression method used in columns (1) to (4) is OLS with event date and firm fixed effects (standard errors clustered by event date); in columns (5) and (6) is Fama-Macbeth regression. The sample used in columns (3) and (4) is a propensity score matched sample. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: OLS		Panel B: PSM		Panel C: Fama-Macbeth	
CAR	[-1,1]	[-10,1]	[-1,1]	[-10,1]	[-1,1]	[-10,1]
Split Ratio	0.154***	0.228***	0.155***	0.238***	0.165***	0.255***
	(16.00)	(16.07)	(12.11)	(12.11)	(9.98)	(8.56)
Split Ratio × LnPrice	**-0.036*** **	**-0.049*** **	**-0.036*** **	**-0.053*** **	**-0.039*** **	**-0.052*** **
	(-11.66)	**(-10.47)**	**(-8.90)**	**(-8.33)**	**(-7.92)**	**(-6.53)**
CAR[-10,-2]	-0.092***		-0.107***		-0.099***	
	(-12.25)		(-7.95)		(-11.59)	
LnPrice	-0.012***	-0.027***	-0.012***	-0.021***	-0.011***	-0.023***
	(-10.06)	(-12.84)	(-4.25)	(-4.10)	(-7.17)	(-5.14)
LnSize	-0.001	-0.003***	0.001	-0.004	0.001	0.001
	(-1.48)	(-2.66)	(0.57)	(-1.35)	(1.47)	(0.47)
LnBM	-0.004***	-0.008***	-0.002	-0.008*	-0.003***	-0.006***
	(-4.73)	(-5.19)	(-1.03)	(-1.91)	(-3.23)	(-5.31)
RunUp	-0.000	0.008***	-0.000	0.005	-0.000	0.008**
	(-0.27)	(3.91)	(-0.07)	(1.21)	(-0.17)	(2.60)
ΔEarnings	-0.008	0.072***	0.011	0.101**	0.035	0.140***
	(-0.86)	(4.67)	(0.37)	(2.07)	(1.31)	(4.37)
ΔDividends	0.146***	0.288***	0.032	0.214*	0.201***	0.342***
	(4.23)	(5.16)	(0.40)	(1.68)	(5.10)	(5.64)
Annual Report	-0.005*	-0.002	-0.007	-0.005	-0.007	-0.007
	(-1.77)	(-0.39)	(-1.55)	(-0.63)	(-1.66)	(-1.40)
ΔIlliquidity	-1.167***	-2.371***	-1.690***	-3.427***	-2.374***	-4.342***
	(-6.66)	(-7.63)	(-3.43)	(-4.06)	(-4.46)	(-4.56)
Event Date Effect	Yes	Yes	Yes	Yes		
Firm Effect	Yes	Yes	Yes	Yes		
Industry Effect					Yes	Yes
R^2/Ave R^2	0.118	0.118	0.196	0.191	0.120	0.156
Observations	23992	23992	6994	6994	24383	24383

Table 13. Time Trend of Split Announcement Effect

This table reports the time trend of the stock split announcement effect. The dependent variable *CAR[-1, 1]* and (*CAR[-10, 1]* are cumulative abnormal returns over the event window [-1, 1] and [-10, 1], respectively. *Split Ratio* is the ratio of newly issued shares from stock splits scaled by original number of shares outstanding. Stock splits are categorized into 3 types based on the magnitude of split ratio. *Small Stock Split* equals 1 if the split ratio is less than 0.5, *Medium Stock Split* equals 1 if the split ratio is within [0.5, 1), and *Large Stock Split* equals 1 if split ratio is greater than or equal to 1. *Time Trend* is an increasing step function mapping each year from 1998 to 2017 into [0, 1]. Other variables are defined in the Appendix A. The regression method used is OLS with event date and firm fixed effects and standard errors are clustered by event date. The sample used in columns (3), (4), (7) and (8) is a propensity score matched sample. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
	Panel A Stock Splits Ratio					Panel B Small, Medium and Large Stock Splits			
	OLS		PSM			OLS		PSM	
CAR	[-1,1]	[-10,1]	[-1,1]	[-10,1]		[-1,1]	[-10,1]	[-1,1]	[-10,1]
Split Ratio	0.052***	0.125***	0.055***	0.134***	Small Stock Split	0.022***	0.031***	0.021***	0.034***
	(10.52)	(17.06)	(7.60)	(12.41)		(7.66)	(6.53)	(4.61)	(4.82)
Split Ratio × Time Trend	**-0.013****	**-0.078*****	**-0.019****	**-0.092*****	Small Stock Split × Time Trend	**-0.013*****	**-0.019****	**-0.013***	**-0.024****
	(-1.99)	**(-7.92)**	**(-2.01)**	**(-6.23)**		**(-2.72)**	**(-2.31)**	**(-1.85)**	**(-2.19)**
					Medium Stock Split	0.039***	0.078***	0.048***	0.086***
						(10.42)	(13.11)	(8.45)	(9.86)
					Medium Stock Split × Time Trend	**-0.020*****	**-0.061*****	**-0.035*****	**-0.069*****
						(-3.45)	**(-6.70)**	**(-4.20)**	**(-5.31)**
					Large Stock Split	0.023***	0.112***	0.023**	0.112***
						(2.85)	(9.29)	(2.32)	(7.65)
					Large Stock Split × Time Trend	0.025**	**-0.054*****	0.023*	**-0.058*****
						(2.50)	**(-3.52)**	(1.80)	**(-2.99)**
Controls	Yes	Yes	Yes	Yes	Controls	Yes	Yes	Yes	Yes
Event Date Effect	Yes	Yes	Yes	Yes	Event Date Effect	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes	Firm Effect	Yes	Yes	Yes	Yes
R^2	0.102	0.103	0.168	0.172	R^2	0.103	0.101	0.168	0.168
Observations	23992	23992	6994	6994	N	23992	23992	6994	6994

Appendix A: Variable Definitions

Variables	Definitions
PV_DS	Stock price relative to intrinsic value following the method of D'Mello and Shroff (2000), where intrinsic value is estimated by residual income valuation model. Residual income is calculated based on the nest 3-year realized income, terminal value is assumed to be average of the last two years residual income, discount rate is estimated by using CAPM.
PV_RRV	
Lockup Expiration	A dummy variable takes value 1 if a firm has IPO or Split Share Structure Reform related restrict stocks lockup expiration in the period of t-3 to t+3 months relative to the stock split announcement month
Share Pledge	A dummy variable takes value 1 if the controlling shareholder of the firm has shares pledged as collateral in banks, security companies or other financial institutions to raise money
CAR[t_1, t_2]	Cumulative abnormal returns across [t_1, t_2], where t_1 and t_2 refer to the t1th and t2th trading days relative to the event date (t=0). In regression analysis, abnormal return is computed by deducting the corresponding 25 value weighted size and book to market ratio independently sorted portfolio return from the raw return.
Update	The difference of analysts' consensus earnings forecasts for the next fiscal year before and after the disclosure of annual profit distribution proposal scaled by the last fiscal year end total equity capitalization
BHAR[s, s+τ]	Buy and hold abnormal return relative to the return of reference portfolio. Individual stock and its corresponding reference portfolio is bought in the beginning of the t_1 month after the profit distribution announcement month and held for 36 months. Reference portfolios used in regression analysis are value weighted, none-rebalanced market, industry and 25 size and book to market ratio independently sorted portfolio.
Split Dummy	A dummy variable equals 1 if a firm discloses stock split and 0 otherwise.
Split Ratio	The ratio of newly issued shares from stock splits scaled by the total outstanding shares before stock splits.
Underperform	A dummy variable equals 1 if the realized earnings in any one of the 3 subsequent fiscal years is below the earnings in the last fiscal year. Or defined by another criterion, equals 1 if the firm's ROA in any one of the 3 subsequent years underperforms the industry average.
LnCoverage	Natural logarithm of 1 plus the total number of analysts who issue analyst reports for the firm.
Institutional Holdings	The ratio of shares held by institutional investors.
LnPrice	Natural logarithm of stock closing price at date t=-11.
Time Trend	An increasing step function mapping year 1998~2017 into [0, 1].
LnSize	Natural logarithm of total tradable equity capitalization.
LnBM	Natural logarithm of book to market ratio.
RunUp	Cumulative stock returns over the past 12 months

ΔIncome	The difference of current fiscal year earnings and the preceding fiscal year earrings scaled by the past fiscal year end total equity capitalization
ΔDividends	The difference of current fiscal year cash dividends and the preceding fiscal year cash dividends scaled by the past fiscal year end total equity capitalization
Annual Report	A dummy variable equals 1 if the profit distribution proposal is disclosed with annual report
ΔIlliquidity	The change of Amihud (2002) illiquidity ratio between (10, 70] post ex-date window and [-70, -10) pre-announcement window if a stock issue stock split, if a stock does not issue stock split, the ex-date is assumed to be 75 days after the profit distribution announcement date, because the average time lag between event date and ex-date.
Earnings Volatility	Standard deviation of earnings scaled by the last fiscal year end equity capitalization in the past three years
3 Year Asset Growth	The difference of between the total assets in the 3rd fiscal year end and the total assets in the last fiscal year end deflated by the total assets in the last fiscal year
3 Year Ave ROA	The average of earnings in the 3 subsequent fiscal year scaled by the total assets in the last fiscal year.