Earnings management and post-split drift

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Abstract

This paper explores whether firms manage their earnings after stock splits to meet the raised expectations from the market due to the positive signal sent by the splits. We first document that post-split drift mainly exists in the first three months and is positively associated with post-split standardized unexpected earnings (SUE). However, the higher post-split SUE of split firms is associated with higher discretionary accruals and abnormally lower R&D expenses. This result is consistent with our hypothesis that split firms overstate their post-split earnings by manipulating accruals and reducing R&D spending. Moreover, post-split abnormal returns increase with discretionary accruals and R&D reduction for about six months and tend to reverse over longer horizons, especially for firms with negative pre-split SUE. Overall, our results indicate that the post-split drift is a short-term phenomenon and partly attributable to the earnings management after the splits.

JEL classification: G12, G14, G30

Keywords: earnings management, stock split, earnings surprise, post-split drift

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1. Introduction

Stock splits are supposed to be cosmetic transactions as only the price per share and shares outstanding change. However, it has been shown to evoke positive price reactions on average, and signaling is one of the most common explanations for stock splits (e.g., Grinblatt, Masulis, and Titman, 1984; McNichols and Dravid, 1990; Nayak and Prabhala, 2001). Stock splits are also costly because transaction costs and brokerage commissions tend to be higher for lower-priced stocks (e.g., Brennan and Copeland 1988; Brennan and Hughes, 1991), and there may be indirect costs associated with false signaling, such as loss of reputation (Pilotte and Manuel, 1996).[1] Based on the costly signal hypothesis, existing studies argue that some managers use splits to convey favorable private information to the market.[2] To be consistent with the signal they sent, managers would have incentives to show superior performance following the split announcements. In this study, we explore whether managers inflate post-split earnings through accruals and real activities management to meet the expectations from the public regarding the split signal.

Meeting earnings expectations helps build credibility with the financial market, maximize their firm's stock price, improve management's reputation, and avoid potential litigation costs triggered by unfavorable earnings surprises (e.g., Bartov, Givoly, and Hayn, 2002; Graham, Harvey, and Rajgopal, 2005). These managerial incentives explain the unexpected increases in earnings associated with stock splits as shown in the previous studies. For example, Lakonishok and Lev (1987) report that the above-normal earnings growth of split firms persists in the first post-split year. Similarly, Ikenberry and Ramnath (2002) find unusually high earnings growth around the time of stock splits. As such, it is plausible that the increase in unexpected earnings could result from managerial incentives to achieve earnings benchmarks, rather than from an

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[1] Brennan and Copeland (1988) argue that the fixed component of the brokerage commissions increases the per-share trading costs of low-priced stocks. Pilotte and Manuel (1996) mention that managers with a reputation of truthful signaling are likely to be believed the next time they signal, while managers who develop a reputation for false signaling are likely to have their next signal discounted and their firm will be penalized by the market.

[2] See, for example, McNichols and Dravid (1990), Brennan and Hughes (1991), and Ikenberry, Rankine, and Stice (1996). Another stream of literature focuses on the trading range/liquidity hypothesis (e.g., Lakonishok and Lev, 1987; Muscarella and Vetsuypens, 1996; Easley, O'Hara, and Saar, 2001; Lin, Singh, and Yu, 2009).

actual surge in profitability in the post-split period. Thus, we conjecture that firms manage post-split earnings upward to meet the higher expectations of the market due to the positive signal sent by the stock splits.[3]

If our conjecture is correct, an interesting question is how post-split abnormal returns are related to the market reaction to the inflated post-split earnings. Existing studies find that earnings management can mislead investors and boost stock prices temporarily (e.g., Rangan, 1998; Teoh, Welch and Wong, 1998) but long-term abnormal returns are negatively associated with abnormal accruals stemming from managerial discretion (e.g., Xie, 2001; Chen and Cheng, 2002). If the market is unable to see through earnings management after the splits, we would observe positive abnormal returns following stock splits that are disproportionate to the content of private information. But when the inflated earnings cannot be sustained and the firms' true values are revealed, return reversals would occur. We, therefore, also conjecture that post-split earnings management is likely a common factor that influences both the increased earnings and stock performance following the splits documented in the literature.

To test the first conjecture, we first re-examine the duration of abnormal returns after split announcements using 12-month calendar-time portfolios. Based on a sample of 9,693 stock splits from 1984 to 2012, we find positive abnormal returns of 22 and 40 basis points per month for value-weighted and equally-weighted portfolios, respectively. However, when examining the post-split horizon month by month, the results show that most of the positive abnormal returns concentrate in the first two to three months. This finding suggests that the post-split drift has a shorter duration than previous studies (e.g., Ikenberry, Rankine, and Stice, 1996; Ikenberry and Ramnath, 2002), which is consistent with Chen, Nguyen, and Singal (2011).

Establishing that the length of the post-split drift is similar to the duration of the SUE effect, we then test whether the abnormal returns following splits are influenced by earnings

[3] Because missing the earnings target (negative surprises) can be penalized by the stock market, as evidenced by the well-known standardized unexpected earnings (SUE) effect that stock prices tend to drift in the same direction as earnings surprises for up to several months (e.g., Bernard and Thomas, 1989).

surprises.[4] Our results show that post-split three-month buy-and-hold abnormal returns (BHAR) are positively related to the post-split SUE but not the pre-split SUE. We further find that for firms with negative pre-split SUE, their average post-split SUE increases and becomes marginally positive; and for firms with positive pre-split SUE, their average post-split SUE decreases but remains positive. This result suggests that post-split earnings may be managed to meet or beat earnings benchmarks in order to meet market expectations regarding the positive signal of stock splits.

Next, we test whether managers use earnings management to boost the numbers after the splits. Earnings management can be conducted via accruals or real activities (e.g., Dechow, Sloan, and Sweeney, 1995; Roychowdhury, 2006; Cohen, Dey and Lys, 2008; Zang, 2011). In particular, Graham et al. (2005) report that managers prefer discretionary expenses reduction (e.g., R&D, advertising, and maintenance) to overstate earnings. Studies also find that R&D reduction is often used to increase short-term earnings (e.g., Dechow and Sloan, 1991; Bushee, 1998; Darrough and Rangan, 2005). We thus focus on discretionary accruals and abnormal R&D expenses as proxies for earnings management. Our results show that split firms have high discretionary accruals and abnormally low R&D expenditures in the year following the splits. These findings are consistent with our conjecture that managers increase accruals management and reduce R&D investment in the post-split period.

Moreover, we find that the average SUE in the year following stock splits increases with post-split discretionary accruals and R&D reduction, consistent with prior studies that earnings management enables firms to achieve positive earnings surprises and avoid reporting earnings decreases (e.g., Burgstahler and Dichev, 1997; Matsumoto, 2002; Burgstahler and Eames, 2006). The results are more pronounced for split firms with negative pre-split SUE, implying that these firms are more likely to manage earnings to create positive earnings surprises after the splits.

[4] Bernard and Thomas (1989) report that most of the post-earnings announcement drift (or the SUE effect) occurs during the first 60 trading days after the earnings announcement (about 3 calendar months), and there is little evidence of significant drift beyond 180 trading days.

For our second conjecture, we find that post-split discretionary accruals and R&D reduction positively affect post-split 6-month BHAR, while discretionary accruals are also significantly negatively related to post-split 18- and 24-month BHAR. This indicates that earnings management boosts short-term returns but may lead to reversals in the long run. As earnings management is more severe in firms with negative pre-split SUE, we expect that they will be penalized by the market for false signaling. Indeed, their abnormal returns become significantly negative after 18 months following the splits. These findings are in line with the previous studies (e.g., Kothari, Mizik, and Roychowdhury, 2016) showing that earnings manipulation results in positive abnormal returns that cannot be sustained once the market recognizes the true value of the firm. Collectively, our results suggest that post-split stock performance is partly attributable to the managerial incentive of meeting the raised market expectations via earnings management.

Finally, we find an increase in sales growth and gross margins in the year following the splits, suggesting that split firms might improve sales through price discounts or more lenient credit terms and increase production to lower costs (Roychowdhury, 2006). This result is consistent with Kothari, Mizik, and Roychowdhury (2016) who argue that the suppression of R&D expenditures not only increases current earnings but also enables a firm to report higher profit margins and cash flow from operations.[5] In addition, we also find that stock splits do not reduce information asymmetry as shown by the increased analyst earnings forecast dispersion following the splits. This result explains why firms are able to manage earnings after stock splits without being detected by the market immediately and in line with Easley, O'Hara, and Saar (2001) and Desai, Nimalendran, and Venkataraman (1998) who point out that stock splits increase the number of both noise and informed traders, resulting in no appreciable improvement in the information environment.

[5]This is not necessarily the case for other manipulation strategies, such as price discounts, channel stuffing, and overproduction to overstate earnings, as these activities can be detrimental for profit margins and contemporaneous abnormal cash flows (see Roychowdhury, 2006).

Our paper contributes to several strands of literature. First, we add to the literature on post-split drift (e.g., Ikenberry, Rankine, and Stice, 1996; Ikenberry and Ramnath, 2002) by showing that the positive post-split abnormal returns are mainly concentrated in the first few months and partly related to the market reaction to the inflated post-split earnings. Second, our paper adds to the literature on earnings management and corporate events. Extant studies find that stock returns associated with many corporate events are influenced by pre-event earnings management (e.g., Teoh, Welch and Wong, 1998; Louis, 2004; Louis and Robinson, 2005). We complement these studies by showing that earnings management after the splits positively affects post-split short-term abnormal returns but also leads to long-term reversals. Third, Ikenberry and Ramnath (2002) argue that analyst earnings forecasts are low at the time of split announcements and forecast revisions are sluggish over time, which can be explained by market underreaction to the information conveyed through stock splits. Our results suggest that it could also be attributed to the increased earnings management after the splits that make analyst earnings forecasts difficult.

2. Data and methodology

2.1. Sample of stock splits

We retrieve all stock splits from CRSP Stock/Events database. To be consistent with prior research (e.g., Ikenberry and Ramnath, 2002), we include only stock splits of five-for-four (split factor of 0.25) or greater and drop all stock dividends, which yields an initial sample of 9,735 stock splits from 1984 to 2012. The sample starts in 1984 because I/B/E/S begins its coverage of analyst forecasts and actual earnings from 1984. We further require a stock split to have a valid effective date within one year of the announcement date, which leaves us with 9,732 splits. After requiring non-missing information on firm size, our final sample includes 9,693 stock splits. The sample size varies across the tests that involve SUE due to the availability of data constructing the SUE measure. In Figure 1, we plot the number of stock splits by year during 1984-2012. The aggregate number of stock splits varies across the years and drops to a lower level after the 2008 financial crisis.

[FIGURE 1 ABOUT HERE]

2.2. Measures of earnings management

Following the prior literature (e.g., Cohen, Dey, and Lys, 2008; Cohen and Zarowin, 2010), we use the modified Jones (1991) model to calculate discretionary accruals. We run the following cross-sectional regression for each industry classified by 2-digit SIC code:

$$\frac{TA_{it}}{Assets_{i,t-1}} = k_1 \frac{1}{Assets_{i,t-1}} + k_2 \frac{\Delta \mathrm{Re}v_{it}}{Assets_{i,t-1}} + k_3 \frac{PPE_{it}}{Assets_{i,t-1}} + \varepsilon_{it} \quad (1)$$

where *TA* represents total accruals defined as earnings before extraordinary items and discontinued operations minus the operating cash flows reported in the statement of cash flows. *Asset* represents total assets, ΔRev is the change in revenues from the preceding year and *PPE* is the gross value of property, plant and equipment. We then use the coefficient estimates from equation (1) to calculate the firm-specific normal accruals (NA_{it}):

$$NA_{it} = \hat{k}_1 \frac{1}{Assets_{i,t-1}} + \hat{k}_2 \frac{(\Delta \mathrm{Re}v_{it} - \Delta AR_{it})}{Assets_{i,t-1}} + \hat{k}_3 \frac{PPE_{it}}{Assets_{i,t-1}} \quad (2)$$

where ΔAR is the change in accounts receivable from the preceding year, which captures potential accounting discretion arising from credit sales. Our measure of discretionary accruals is the difference between total accruals and the fitted normal accruals.

We adopt the model of Kothari, Mizik, and Roychowdhury (2016) and estimate abnormal R&D expenditures as follows:

$$R\&D_{i,t} = \alpha_{rd,\, i} + \Delta_{rd,\, t} + \beta_1 R\&D_{i,t-1} + \beta_2 Sales_{i,t-1} + \varepsilon_{i,t}, \quad (3)$$

where subscript *i* and *t* denote firm and year. *R&D* is the value of the size-adjusted R&D expenses. *Sales* is the value of size-adjusted sales. To control for firm and year effects, we employ the following steps. First, each firm's annual R&D expenses are differenced from the cross-sectional mean for that year. Second, for each firm, the annual deviation of R&D from the cross-sectional mean is differenced from the corresponding deviation in the previous year. The explanatory variable *Sales* is also differenced twice in the same way. We then estimate the model using panel data, which yields a time-series of residuals for each firm. We subtract from each firm-year residual the mean value of the residual across all years for the firm to obtain abnormal R&D.

2.3. Measures of return drifts

We measure return drifts using two approaches: BHAR and calendar-time portfolio regression. BHAR is a popular approach in the literature because it represents the returns that a long-horizon investor can earn, and its interpretation is straightforward. However, BHAR suffers from poor statistical properties and may overstate the long-run abnormal performance (see, e.g., Fama, 1998; Mitchell and Stafford, 2000). The calendar-time portfolio approach does not suffer from these problems, because the time-series variation of portfolio returns can accurately capture the effect of correlation across event stocks (Fama, 1998).

For calendar-time portfolio regression, in each month from 1984 to 2013, we form the split portfolio by including firms that have made split announcements in the past x months, where x ranges from 1 to 12. We regress portfolio returns on either Fama and French's (1993) three factors, Carhart's (1997) four factors, or five factors by including the liquidity factor based on Pastor and Stambaugh (2003) as

$$R_p - R_f = a + b\,(R_m - R_f) + s\,SMB + h\,HML + m\,MOM + q\,LIQ + e_p, \tag{4}$$

where R_p is the stock split portfolio return, R_f is the risk-free rate, R_m is the market portfolio return, *SMB* is the small-firm portfolio return minus the big-firm portfolio return, *HML* is the high B/M portfolio return minus the low B/M portfolio return, *MOM* is the past winner portfolio return minus the past loser portfolio return, and *LIQ* is the low liquidity portfolio return minus the high liquidity portfolio return. The regression intercept *a* measures the average monthly abnormal return on the stock split portfolio. We perform *t*-tests on intercepts based on heteroskedasticity- and autocorrelation-corrected standard errors using Newey and West's (1987) method.

Previous studies argue that abnormal returns (if any) of corporate events may concentrate in small stocks (Fama, 1998; Brav, Geczy, and Gompers, 2000). Therefore, we implement the calendar-time portfolio approach by applying both equal-weighted and value-weighted formation strategies. To address the concern that the calendar-time approach may have low power to detect abnormal returns when the events are clustered in some specific time periods (Loughran and Ritter, 2000), we follow Ikenberry and Ramnath (2002) and perform both ordinary least squares (OLS) and weighted least squares (WLS) regressions where the weight for the WLS regressions is based on the number of stocks in a given month.[6]

For robustness checks, we also use Ibbotson's (1975) returns across time and securities approach to estimate abnormal returns for the full stock-split sample. We run cross-sectional regressions with Carhart's (1997) four factors in each event month and then add the monthly abnormal returns (regression intercepts) over event months. The results are similar to what we obtain from the calendar-time approach. For brevity, we do not report the results.

3. Empirical Results

3.1. Post-split return drift by event months

We first examine the post-split drift by different horizons using the calendar-time approach. We report the results based on the five-factor model, but the unreported results are qualitatively similar using the three-factor or four-factor model. In Panel A of Table 1, we show the monthly abnormal returns over 3, 6, and 12 months following split announcements. Based on

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[6] Calendar months with less than five stocks in the portfolio are excluded from the regression. The results are similar if we require the minimum observation to be 1 or 10.

9,693 stock splits during the period 1984-2012, we find that the post-split abnormal returns are significantly positive, with approximately 40 (22) basis points per month for 12 months in the equal- (value-) weighted portfolios using the WLS regressions, after controlling for size, book-to-market, momentum, and liquidity.

Although we confirm the positive return drift in the first post-split year (see Internet Appendix Table IA1 for more details), the results in Panel B show that the abnormal returns are not uniformly distributed among the 12 months after the splits. Most of the abnormal returns occur in the first few months after split announcements. For example, in the WLS regressions, the equal-weighted and value-weighted three-month abnormal returns are 1.13% and 0.47% per month, respectively (Panel A), but no significant positive abnormal returns are observed for event months 8 to 11 (Panel B).

[TABLE 1 ABOUT HERE]

In Figure 2, we plot the equal-weighted abnormal returns over 12 months after splits. The abnormal return declines sharply in the third month after the splits and approaches zero after the eighth month (except for the month 12). These results suggest that post-split drift mainly concentrates in the first few months, consistent with the findings in Chen, Nguyen, and Singal (2011).

[FIGURE 2 ABOUT HERE]

3.2. Relation between post-split drift and SUE

Since the post-split drift lasts for three to seven months, and the duration of the SUE effect is shown to be between three to six months, we examine whether the post-split drift is related to the SUE effect. Following Livnat and Mendenhall (2006), we define the SUE as actual earnings minus expected earnings, scaled by stock price at the end of the quarter. The measure of analyst earnings expectations is the median of forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement, considering only the most recent forecast of each analyst. We test whether earnings surprises explain post-split abnormal returns by performing the following regression:

$$BHAR_{j,t+3,\, t+63} = \beta_0 + \beta_1\, Post\text{-}split\ SUE_j + \beta_2\, Pre\text{-}split\ SUE_j + \delta' X_j + \varepsilon_j, \tag{5}$$

where subscript *j* and *t* denote the stock split *j* announced on day *t*. The dependent variable is the three-month BHAR starting from day *t*+3 following the announcement, adjusted by subtracting the return on a benchmark portfolio matched on size, B/M, and momentum (see Daniel, Grinblatt, Titman, and Wermers, 1997; DGTW hereafter).[7] *Pre*- and *Post-split SUE* are earnings surprises before and after the split. We also control for size, B/M ratio, momentum, the pre-split stock price level, and change in liquidity around stock splits in the regressions.

In Table 2, we find that post-split SUE is positively related to post-split three-month BHAR, while pre-split SUE does not have a significant coefficient. In addition, post-split abnormal returns are positively related to the improvement in liquidity (i.e., negative coefficient of changes in illiquidity), consistent with the findings in Lin, Singh, and Yu (2009).

[TABLE 2 ABOUT HERE]

3.3. Earnings management after stock splits

A stock split would be a more credible signal to investors when it is accompanied by superior performance following the announcement. Managers who are under pressure to meet the market's expectations for earnings would have incentives to play earnings surprise games by managing earnings upward.

To test this conjecture, we first investigate whether split firms experience significant changes in SUE after the splits. In Table 3, we calculate the average value of SUE one-year before and after split announcements as well as the average changes in SUE around the splits. For firms with negative pre-split SUE, their average SUE increases from −0.0048 (t-stat = −4.80)

[7] The results are similar when we use the CRSP value-weighted market return as the benchmark return for the BHAR.

to 0.0002 (t-stat = 0.17). The change in SUE is 0.005 and significant (t-stat = 3.30). For firms with positive pre-split SUE, their average post-split SUE decreases but remains positive with an average value of 0.0002 (t-stat = 4.35). The result indicates that split firms report marginally positive SUE after the splits, providing the first suggestive evidence that managers may manipulate earnings after stock splits to meet or beat earnings benchmark.

[TABLE 3 ABOUT HERE]

Next, we directly test whether some managers engage in earnings management after the splits. Prior research shows that firms manage earnings through accrual manipulation and real activities such as reducing R&D expenses (e.g., Dechow and Sloan, 1991; Dechow, Sloan, and Sweeney, 1995; Darrough and Rangan, 2005; Graham et al., 2005; Roychowdhury, 2006; Cohen, Dey and Lys, 2008). Hence, we use discretionary accruals and abnormal R&D expenditures as proxies for earnings management and perform the following regression:

$$EM_{i,t} = \beta_0 + \beta_1 Split_{i,t-1} + \delta' X_{i,t-1} + Firm\ fixed\ effect + Year\ fixed\ effect + \varepsilon_{i,t}, \tag{6}$$

where subscript i and t denote firm and year, respectively. The dependent variable EM is discretionary accruals or abnormal R&D expenses, which are calculated using the modified Jones (1991) model and the model of Kothari, Mizik, and Roychowdhury (2016), respectively. *Split* is a dummy equal to one if the firm has split announcement in year t–1. We estimate this regression using all Compustat firms with non-missing information on earnings management and other control variables over the period 1984-2012.

In Table 4, the coefficients on split dummy are 0.008 for the regression of discretionary accruals in column 1 and −0.003 for abnormal R&D expenses in column 2, and both are statistically significant. The result shows that split firms have high discretionary accruals and abnormally low R&D expenditures in the year following the splits, suggesting that managers tend to manage accruals and reduce R&D spending after stock splits to boost earnings numbers.

[TABLE 4 ABOUT HERE]

As we have shown that post-split abnormal returns are related to post-split SUE, we further examine whether post-split SUE is related to earnings management. In Table 5, we regress the average SUE in the year following stock splits on the two measures of earnings management and find that post-split SUE is positively associated with post-split discretionary accruals and negatively related to post-split abnormal R&D expenses.

Moreover, in columns 3 and 4 of Table 5, we show that firms with negative pre-split SUE (*Negative pre-split SUE dummy*) are more likely to engage in earnings management to inflate earnings after the splits. Hence, these results together with that in Table 3, indicate that managers are likely to create small positive earnings surprises through accruals management and R&D reduction after stock splits to meet the market expectations regarding the positive signal of stock splits.

[TABLE 5 ABOUT HERE]

3.4. Post-split abnormal returns and earnings management

We have shown that earnings management increases after stock splits, causing a rise in the post-split SUE. Given that earnings management can be used to temporarily boost stock prices (e.g., Rangan, 1998; Teoh, Welch, and Wong, 1998), we test whether post-split abnormal returns are at least partly attributable to earnings management in this subsection. Specifically, we regress post-split BHAR over different horizons on the two earnings management measures.

Table 6 shows that the coefficient on post-split discretionary accruals is significantly positive for post-split 6-month BHAR (DGTW-adjusted) but becomes significantly negative for post-split 18- and 24-month BHAR. Meanwhile, the coefficient on abnormal R&D expenses is significantly negative only for post-split 6-month BHAR. These results suggest that accruals management and R&D reduction are positively related to short-term returns after splits, but may also result in long-term reversals when the inflated earnings cannot be sustained or true earnings are revealed. Our findings are in line with prior research suggesting that firms with high discretionary accruals have relatively low stock returns in the future (e.g., Xie, 2001; Chen and Cheng, 2002).

[TABLE 6 ABOUT HERE]

As discussed in the previous section, firms with negative pre-split SUE seem to have more earnings management after the splits. We thus examine whether their post-split stock performance differs from those with positive pre-split SUE. For each split, we first calculate the average value of SUE over one year before the split announcement. Then, we classify 5,690 stock splits (with non-missing SUE and post-split BHAR) into two groups: 1,345 splits with pre-split SUE smaller or equal to zero and 4,345 splits with pre-split SUE larger than zero. For each group, we calculate the average DGTW-adjusted BHAR following split announcements over different horizons.

As reported in Table 7, for firms with negative pre-split SUE, post-split 6-month BHAR is 2.22 (with a *t*-stat of 2.87), while post-split 18- and 24-month BHAR are −3.34 (with a *t*-stat of −2.52) and −4.37 (with a *t*-stat of −2.68), respectively. For firms with positive pre-split SUE, their average post-split BHAR remains positive but becomes insignificant after 12 months following split announcements. Collectively, these results suggest that firms that manage earnings to meet/beat earnings benchmarks after the splits are likely to experience return reversals in the long run. And the pattern is more prominent for the firms with negative pre-split SUE.

[TABLE 7 ABOUT HERE]

4. Additional tests and robustness checks

4.1. Operational activities after stock splits

Graham et al. (2005) find that managers prefer real activities manipulation, such as reducing discretionary expenditures or capital investments, to manage earnings. We have shown that split firms tend to increase earnings by manipulating accruals and reducing R&D expenditures. Kothari, Mizik, and Roychowdhury (2016) argue that the reduction of R&D expenditures enables firms to increase current earnings and report higher profit margins and operating cash flows. This is not necessarily the case for other strategies to manipulate earnings, such as price discounts, channel stuffing, and overproduction, as these activities have a negative effect on profit margins and contemporaneous abnormal cash flows (Roychowdhury, 2006). In this section, we thus examine how their operational activities change after splits by using the following regression:

$$Operations_{i,t} = \beta_0 + \beta_1\, Split_{i,t-1} + \delta' X_{i,t-1} + Firm\ fixed\ effect + Year\ fixed\ effect + \varepsilon_{i,t}, \qquad (7)$$

where subscript *i* and *t* denote firm and year, respectively. *Operations* represents one of the three variables*:* R&D/Sales, sales growth, or gross margins. *R&D/Sales* is R&D expenses divided by sales. *Sales growth* is sales in year *t* minus sales in year *t*−1, divided by sales in year *t*−1. *Gross margin* is calculated as the year *t* net sales less cost of goods sold for the year, scaled by net sales. *Split* is a dummy equal to one if the firm has a stock split in year *t*–1. All regressions control for firm and year fixed effects.

Table 8 shows that the coefficients on the split dummy are −0.008 for the regression of R&D investments, 0.054 for sales growth, and 0.019 for gross margins. This is consistent with our argument that managers reduce R&D expenditures after stock splits to increase current earnings, profit margins, and operating cash flows. Accordingly, their firm's R&D investments decrease, and sales growth and gross margins increase in the year following splits. This also suggests that managers of split firms may manage earnings by improving sales through price discounts or more lenient credit terms and overproducing to lower costs (Roychowdhury, 2006)

[TABLE 8 ABOUT HERE]

4.2. Changes in analyst earnings forecast dispersion

A firm's information environment is related to its ability and means for managers to signal information to the market. The extent to which earnings management succeeds in misleading investors partly hinges on its relative opacity, i.e., the degree to which outside investors can detect and unravel earnings management. To examine the changes in the information environment around splits, we use analyst earnings forecast dispersion as a proxy for uncertainty about future earnings as it represents the consensus among analysts regarding future firm prospects. Analyst dispersion is defined as the standard deviation of earnings forecasts scaled by the absolute value of the mean earnings forecast (e.g., Diether, Malloy, and Scherbina, 2002).

For each of 6,037 stock splits (with non-missing information on the pre-split SUE), earnings forecast dispersion is calculated over the 3, 6, 9, and 12 months before and after the split. We use earnings forecasts for the current and next three fiscal quarters (I/B/E/S forecast period indicator (FPI) = 6, 7, 8, or 9). We then calculate the changes in forecast dispersion as the difference in forecast dispersion before and after the split. These split firms are further divided into two groups: 1,449 splits with pre-split SUE smaller than or equal to zero and 4,588 splits with pre-split SUE larger than zero. We calculate the average changes in analyst forecast dispersion for these two groups separately. Split firms that do not have earnings forecasts issued by analysts are excluded.

Table 9 reports that analyst forecast dispersion increases for at least 9 months following stock splits, suggesting that stock splits increase information uncertainty. This result is consistent with the previous findings that stock splits do not reduce information asymmetry (Easley, O'Hara, and Saar, 2001; Desai, Nimalendran, and Venkataraman, 1998) and could explain why managers are able to manage earnings to meet or beat earnings expectations after stock splits.

[TABLE 9 ABOUT HERE]

4.3. Further suggestive evidence

We have shown that the post-split abnormal returns are related to the post-split SUE, particularly for the firms exhibiting a tendency of earnings management. In this subsection, we explore further the relation between stock returns and SUE for the split and non-split firms using a double sort portfolio approach. Specifically, we first calculate 3-month BHAR (DGTW-adjusted) from day t+2 to t+63 following earnings announcements and sort all earnings announcements into SUE quintiles by quarter. Within each SUE quintile, we then classify firms into split and non-split subsamples depending on whether firms have stock splits in the three months before the earnings announcement. In addition, each split firm is matched with a non-split firm in the same SUE quintile and with the closest size, B/M, and return momentum (prior 11-month cumulative return from month –12 to –2) to the split firm at the previous month end before the earnings announcement. Internet Appendix Table IA2 shows that for non-split firms, SUE is positively and monotonically associated with abnormal returns, which is consistent with the literature. However, split firms do not exhibit such a pattern. We obtain similar results based on matched non-split firms. This distinct relation between stock returns and SUE for split firms could be at least partially attributed to the managerial incentives to manipulate earning after splits.

Moreover, Table IA3 reports the same analysis based on Fama-MacBeth cross-sectional regressions instead of double sorting. We define a split dummy that equals one if the firm has a stock split in the past three months, and use five dummies for SUE quintiles, where *SUE* is in the most recent quarter. We find that the coefficient on the interaction term of split dummy with the lowest SUE quintile dummy is significantly positive. Given our findings that firms with negative pre-split SUE are more likely to manage earnings upward after splits and their average post-split 3-month BHAR is significantly positive, this result provides another suggestive evidence in line with our earnings manipulation explanation.

4.4. Robustness checks on post-split return drift

Although a large body of prior studies document a positive drift following stock splits (e.g., Ikenberry, Rankine, and Stice, 1996; Desai and Jain, 1997; Ikenberry and Ramnath, 2002), Fama (1998) and Byun and Rozeff (2003) argue that the post-split abnormal returns are spurious, which may disappear under different sample selections, sample periods, or methods used to estimate abnormal returns. In Table IA1, we find significant and robust positive abnormal returns based on 12-month calendar-time portfolios following the splits for three different periods: 1984-2012, 1963-2012, and 1927-2012. We further divide our sample into two subperiods 1984-1997 and 1998-2012, and find that the positive post-split abnormal returns exist for both sub-periods based on 3- and 4-factor models. We also show that post-split abnormal returns are much stronger during the period 1984-1997, compared with the period 1998-2012.

In addition, we employ the q-factor model by Hou, Xue, and Zhang (2015), which consists of the market factor, size factor, investment factor, and return-on-equity factor. We repeat the analysis in Table 1 and find consistent results as reported in Table IA4.

5. Conclusion

This study sheds light on the post-split drift puzzle by providing a new explanation. We find that post-split stock performance is partly attributable to the influence of earnings management after the splits. Our results indicate that post-split abnormal returns are related to the SUE. We further show that split firms tend to report small positive earnings surprises after splits, and have high discretionary accruals and abnormally low R&D expenses in the year following splits. Moreover, post-split SUE increases with discretionary accruals and R&D reduction, especially for firms with negative pre-split SUE. These results suggest that some managers may inflate earnings through accruals management and R&D reduction in the post-split period in an attempt to meet or beat earnings expectations to be consistent with the positive signal sent by the stock split.

We also show that post-split abnormal returns increase with discretionary accruals and R&D reduction for about six months and tend to reverse over longer horizons, especially for firms with negative pre-split SUE. Our results are consistent with prior research suggesting that earnings management appears to temporarily boost stock prices and also lead to long-term return reversals. In addition, we also find that analyst earnings forecast dispersion increases after splits. This increased information uncertainty might explain why managers are able to manipulate earnings after stock splits without being detected by the market immediately. Overall, our findings suggest that earnings management helps explain post-split drift and the unexpected increase in post-split earnings as documented in the literature.

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Table 1
Post-split abnormal returns by different horizons

This table reports post-split abnormal returns (in %) over different investment horizons based on the sample of 9,693 stock splits during 1984-2012. The abnormal returns (alphas) are estimated using the calendar-time portfolio regression based on a five-factor model that includes the liquidity factor from Pastor and Stambaugh (2003) into the Carhart's (1997) four-factor model. In each calendar month, a portfolio is formed of firms that had stock split announcements in the past 3, 6, or 12 months (Panel A) or firms that made split announcements in the *x*th (where *x* takes a value from 1 to 12) month before (Panel B). Monthly portfolio returns are either equal-weighted (EW) or value-weighted (VW, weighted by market value at the end of the previous month). Both ordinary least squares (OLS) and weighted least squares (WLS) methods are used to run regressions, where the weight for WLS is the number of splits included in the portfolio in each month. Calendar months with less than 5 stocks in the portfolio are excluded from the regression. Numbers in parentheses are *t*-statistics based on Newey-West (1987) standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	OLS				WLS			
	EW		VW		EW		VW	
Horizon/ Event month	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat
Panel A: By different investment horizons								
(+1, +3)	0.95***	(5.66)	0.50**	(2.42)	1.13***	(8.85)	0.47**	(2.46)
(+1, +6)	0.53***	(3.15)	0.23	(1.27)	0.69***	(6.03)	0.33**	(2.15)
(+1, +12)	0.36***	(2.62)	0.26*	(1.66)	0.40***	(3.25)	0.22**	(2.01)
Panel B: By event months								
1	1.76***	(6.37)	0.64**	(2.17)	2.01***	(10.17)	0.67***	(2.60)
2	1.00***	(5.22)	0.81***	(3.14)	1.03***	(5.47)	0.74***	(3.03)
3	0.26	(1.30)	0.23	(0.95)	0.37*	(1.94)	0.17	(0.74)
4	0.22	(1.26)	-0.11	(-0.51)	0.16	(1.08)	-0.07	(-0.34)
5	0.22	(1.10)	0.72**	(2.07)	0.24	(1.29)	0.60**	(2.28)
6	0.30*	(1.73)	0.43	(1.53)	0.27*	(1.67)	0.34	(1.36)
7	0.41*	(1.66)	0.42	(1.54)	0.34*	(1.76)	0.23	(1.01)
8	-0.03	(-0.16)	-0.05	(-0.16)	0.05	(0.24)	0.22	(1.00)
9	-0.22	(-1.17)	0.17	(0.68)	-0.27	(-1.27)	0.25	(1.21)
10	0.23	(1.02)	0.54**	(2.05)	0.05	(0.24)	0.28	(1.17)
11	-0.02	(-0.10)	-0.19	(-0.76)	-0.13	(-0.66)	-0.53**	(-2.31)
12	0.57***	(2.64)	0.68**	(2.06)	0.36*	(1.72)	0.34	(1.52)

Table 2

Post-split three-month abnormal returns and standardized unexpected earnings (SUE)

This table presents the regression of post-split three-month buy-and-hold abnormal returns (BHAR) on standardized unexpected earnings (SUE) and control variables. The regression is: $BHAR_{j,t+3,\,t+63} = \beta_0 + \beta_1\, Post\text{-}split\ SUE_j + \beta_2\, Pre\text{-}split\ SUE_j + \delta' X_j + \varepsilon_j$, where subscript *j* and *t* denote the stock split *j* announced on day *t*. The dependent variable is the three-month BHAR starting from day *t*+3 following the split announcement, adjusted by subtracting the returns on a benchmark portfolio matched on size, B/M, and momentum (Daniel, Grinblatt, Titman, and Wermers 1997). *Pre-* and *Post-split SUE* are earnings surprises before and after the split. SUE is based on I/B/E/S reported analyst forecasts and actual earnings as in Livnat and Mendenhall (2006), defined as actual earnings minus expected earnings, scaled by stock price. The measure of analyst expectations is the median of forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement, considering only the most recent forecast of each analyst. *Size* is the natural logarithm of pre-split market capitalization in millions. *B/M* is the pre-split book-to-market ratio from Compustat, book value of equity divided by market value of equity. *Momentum* is the pre-split 11-month cumulative return from month –12 to –2. *Ln(Price)* is the natural logarithm of the stock price at day *t*–3 relative to the split announcement. *Illiquidity* is Amihud's (2002) illiquidity measure defined as the average ratio of the daily absolute return to its dollar trading volume. *Change in Illiquidity* is the difference between pre-split illiquidity estimated over three months before the split announcement date and post-split illiquidity estimated over three months after the effective date. Numbers in parentheses are White (1980) heteroskedasticity-adjusted standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
Post-split SUE	3.255***		3.527***
	(0.836)		(0.896)
Pre-split SUE		-0.748	-1.248
		(0.841)	(0.876)
Size	-0.015***	-0.016***	-0.015***
	(0.003)	(0.003)	(0.003)
B/M	-0.030***	-0.027***	-0.029***
	(0.009)	(0.009)	(0.009)
Momentum	0.007	0.008	0.008
	(0.007)	(0.007)	(0.007)
Ln(Price)	0.026***	0.028***	0.026***
	(0.009)	(0.009)	(0.009)
Change in Illiquidity	-0.044***	-0.046***	-0.044***
	(0.007)	(0.007)	(0.007)
Year fixed effect	Yes	Yes	Yes
Observations	4,842	4,842	4,842
Adjusted R^2	0.020	0.018	0.021

Table 3

Changes in standardized unexpected earnings (SUE) around splits

This table shows the average value of SUE in the one-year before and after split announcements as well as the average changes in SUE around splits. In our sample of 9,693 splits, 5,884 splits have non-missing data of pre- and post-split SUE. We divide these splits into two groups: 1,392 splits with pre-split average SUE<=0 and 4,492 splits with pre-split average SUE>0. Panel A reports mean (also *t*-statistic) and median of the average SUE, SUE decile rank, and absolute SUE in the one-year before and after stock splits. Panel B shows mean and median of the changes in the average SUE, SUE decile rank, and absolute SUE before and after splits. *N* is the number of splits.

Panel A: Summary statistics of average SUE before and after splits

		1-year before split			1-year after split		
		Mean	*t*-stat	Median	Mean	*t*-stat	Median
Splits with pre-split SUE<=0	Average SUE	-0.0048	-4.80	-0.0008	0.0002	0.17	0.0000
(N=1392)	Average SUE decile rank	3.3766	97.06	3.5000	4.2985	94.03	4.3333
	Average absolute SUE	0.0058	5.77	0.0015	0.0043	3.09	0.0014
Splits with pre-split SUE>0	Average SUE	0.0021	26.86	0.0009	0.0002	4.35	0.0003
(N=4492)	Average SUE decile rank	5.8282	283.43	5.7500	4.7033	210.61	4.6667
	Average absolute SUE	0.0024	27.74	0.0012	0.0020	33.77	0.0010

Panel B: Summary statistics of changes in SUE around splits

		Mean	*t*-stat	Median
Splits with pre-split SUE<=0	Change in SUE	0.0050	3.30	0.0008
(N=1392)	Change in SUE decile rank	0.9219	17.63	0.7500
	Change in absolute SUE	-0.0015	-0.86	-0.0001
Splits with pre-split SUE>0	Change in SUE	-0.0018	-20.06	-0.0006
(N=4492)	Change in SUE decile rank	-1.1249	-43.93	-1.0000
	Change in absolute SUE	-0.0004	-5.24	-0.0001

Table 4

Earnings management after stock splits

This table presents the effect of stock splits on earnings management during the period 1984-2012. The regression is: $Earnings\ management_{i,t} = \beta_0 + \beta_1\,Split_{i,t-1} + \delta' X_{i,t-1} + Firm\ fixed\ effect + Year\ fixed\ effect + \varepsilon_{i,t}$, where subscript *i* and *t* denote firm and year, respectively. The dependent variable is one of the following: 1) accruals-based earnings management, discretionary accrual from modified Jones (1991) model; 2) abnormal R&D expenses estimated from the model of Kothari, Mizik, and Roychowdhury (2016). *Split* is a dummy equal to one if the firm has split announcement in year *t*–1. *Size* is the natural logarithm of market capitalization in millions. *Sale* is the natural logarithm of sales. *M/B* is the market-to-book ratio from Compustat, defined as the market value of assets over the book value of assets. *ROA* is return on assets, defined as operating income before depreciation divided by book value of total assets. *Capital expenditure* is the ratio of capital expenditure to the total asset. *Leverage* is the total debt (debt in current liabilities plus long-term debt) divided by total assets. *Cash flow* is cash flow to total assets. *Tangibility* is the ratio of property, plant, and equipment to book value of total assets. All regressions control for firm and year fixed effects. Numbers in parentheses are two-way clustered standard errors by firm and year (Petersen, 2009). ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent var.	Discretionary accruals	Abnormal R&D
	(1)	(2)
Split	0.008***	-0.003***
	(0.002)	(0.001)
Size	-0.006***	0.005***
	(0.002)	(0.001)
Sale	-0.006***	-0.016***
	(0.002)	(0.001)
M/B	0.005***	-0.003***
	(0.001)	(0.001)
ROA	0.134***	0.015**
	(0.017)	(0.007)
Capital expenditure	-0.013	0.018**
	(0.011)	(0.008)
Leverage	-0.029***	-0.008**
	(0.009)	(0.004)
Cash flow	-0.051***	-0.015**
	(0.018)	(0.007)
Tangibility	-0.015	0.002
	(0.010)	(0.006)
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	120,031	66,141
Adjusted R^2	0.242	0.537

Table 5

Post-split SUE and earnings management

This table shows the relation between the post-split SUE and earnings management. The dependent variable is the average SUE in the year following stock splits. Post-split earnings management is measured as discretionary accrual from modified Jones (1991) model and abnormal R&D expenses estimated from the model of Kothari, Mizik, and Roychowdhury (2016). For each split, we calculate the average value of SUE over one year before the split. *Negative pre-split SUE dummy* equals one for a split firm with negative pre-split SUE. All regressions control for year fixed effects. Numbers in parentheses are White (1980) heteroskedasticity-adjusted standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	Dependent variable: Post-split SUE			
	(1)	(2)	(3)	(4)
Discretionary accruals	0.094*		0.004	
	(0.052)		(0.003)	
Abnormal R&D		-0.389**		-0.191
		(0.166)		(0.179)
Discretionary accruals × Negative pre-split SUE dummy			0.208*	
			(0.120)	
Abnormal R&D × Negative pre-split SUE dummy				-1.115***
				(0.422)
Negative pre-split SUE dummy			-0.085***	-0.018
			(0.016)	(0.024)
Size	-0.007	0.006	-0.006	0.006
	(0.009)	(0.009)	(0.009)	(0.009)
Sale	0.014*	0.014	0.012	0.012
	(0.008)	(0.009)	(0.008)	(0.009)
B/M	-0.013	-0.031	-0.010	-0.019
	(0.039)	(0.047)	(0.039)	(0.047)
Momentum	-0.001	0.016**	-0.003	0.013*
	(0.008)	(0.007)	(0.008)	(0.007)
ROA	-0.035	-0.293*	-0.046	-0.287*
	(0.145)	(0.151)	(0.145)	(0.151)
Capital expenditure	0.197	-0.120	0.219	-0.115
	(0.136)	(0.186)	(0.136)	(0.185)
Leverage	0.050	-0.058	0.060	-0.057
	(0.043)	(0.053)	(0.043)	(0.053)
Cash flow	-0.096	0.270	-0.108	0.230
	(0.190)	(0.191)	(0.190)	(0.191)
Tangibility	-0.099**	0.031	-0.096**	0.043
	(0.045)	(0.061)	(0.045)	(0.061)
Change in Illiquidity	-0.037***	-0.089***	-0.037***	-0.091***
	(0.014)	(0.020)	(0.014)	(0.020)
Year fixed effect	Yes	Yes	Yes	Yes
Observations	4,321	2,486	4,321	2,486
Adjusted R^2	0.024	0.015	0.030	0.022

Table 6

Post-split BHAR and earnings management

This table shows the relation between the post-split BHAR and earnings management. Post-split BHAR (DGTW-adjusted) is calculated over the *x*-month period (where *x* equals 6, 9, 12, 18, or 24) following split announcement on day *t*, starting from day *t*+3. Post-split earnings management is measured as discretionary accruals from modified Jones (1991) model or abnormal R&D expenses estimated from the model of Kothari, Mizik, and Roychowdhury (2016) in the year following the split announcement. Numbers in parentheses are White (1980) heteroskedasticity-adjusted standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	Dependent variable: Post-split BHAR									
	6 months	9 months	12 months	18 months	24 months	6 months	9 months	12 months	18 months	24 months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Discretionary accruals	0.012**	-0.088	-0.092	-0.183*	-0.231**					
	(0.005)	(0.067)	(0.077)	(0.107)	(0.115)					
Abnormal R&D						-0.539**	-0.415	-0.072	0.233	0.823
						(0.241)	(0.341)	(0.395)	(0.515)	(0.780)
Size	-0.005	0.005	-0.001	0.008	0.005	0.001	0.013	0.010	0.006	0.030
	(0.007)	(0.009)	(0.010)	(0.013)	(0.015)	(0.011)	(0.014)	(0.015)	(0.021)	(0.033)
Sale	0.001	-0.007	0.004	0.001	0.003	-0.001	-0.011	-0.006	0.004	-0.013
	(0.006)	(0.009)	(0.010)	(0.013)	(0.015)	(0.010)	(0.014)	(0.015)	(0.021)	(0.028)
B/M	0.029	0.014	0.003	0.061	0.109	0.094*	0.069	0.066	0.121	0.552
	(0.029)	(0.036)	(0.044)	(0.055)	(0.069)	(0.054)	(0.062)	(0.077)	(0.097)	(0.376)
Momentum	-0.006	-0.003	0.004	0.001	-0.011	0.006	0.003	0.010	0.014	-0.015
	(0.009)	(0.011)	(0.012)	(0.015)	(0.016)	(0.008)	(0.013)	(0.014)	(0.019)	(0.029)
ROA	-0.198*	-0.288*	-0.145	-0.384*	-0.266	-0.355**	-0.474**	-0.536**	-0.870***	-0.775**
	(0.112)	(0.148)	(0.205)	(0.221)	(0.282)	(0.179)	(0.196)	(0.240)	(0.295)	(0.379)
Capital expenditure	0.038	-0.039	-0.101	-0.058	-0.174	0.142	0.026	-0.002	0.341	1.137
	(0.107)	(0.132)	(0.157)	(0.201)	(0.243)	(0.202)	(0.251)	(0.301)	(0.386)	(0.744)
Leverage	-0.035	0.007	0.018	0.002	0.060	0.004	0.067	0.076	0.099	0.005
	(0.034)	(0.045)	(0.055)	(0.070)	(0.086)	(0.059)	(0.075)	(0.094)	(0.118)	(0.271)
Cash flow	0.475***	0.698***	0.576**	1.082***	1.200***	0.705***	1.035***	1.059***	1.670***	1.528***
	(0.161)	(0.210)	(0.288)	(0.304)	(0.380)	(0.227)	(0.261)	(0.324)	(0.384)	(0.521)
Tangibility	-0.001	0.004	-0.006	-0.055	-0.074	-0.108	-0.060	-0.030	-0.171	-0.429*
	(0.031)	(0.039)	(0.047)	(0.060)	(0.076)	(0.067)	(0.074)	(0.091)	(0.117)	(0.239)
Change in Illiquidity	-0.043***	-0.051***	-0.055***	-0.061***	-0.075**	-0.073***	-0.088***	-0.080**	-0.101**	-0.316
	(0.012)	(0.015)	(0.018)	(0.023)	(0.033)	(0.021)	(0.030)	(0.036)	(0.047)	(0.234)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,122	4,100	4,077	3,964	3,946	2,383	2,367	2,350	2,278	2,268
Adjusted R^2	0.012	0.014	0.009	0.015	0.016	0.022	0.026	0.026	0.028	0.020

Table 7

Post-split BHAR: Sorted by pre-split SUE

This table shows the average BHAR (in %) following stock splits sorted by the pre-split average SUE. For each split, we first calculate the average value of SUE over one year before the split. We classify 5,690 stock splits (with non-missing SUE data and BHAR following splits) into two groups: 1,345 splits with pre-split SUE<=0 and 4,345 splits with pre-split SUE>0. *BHAR* (DGTW-adjusted) is calculated over the *x*-month period (where *x* equals 3, 6, 9, 12, 18, or 24) following split announcement on day *t*, starting from day *t*+3. *N* is the number of stock splits. Numbers in parentheses are *t*-statistics based on two-sided *t*-tests. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

		Post-split BHARs						
		3 months	6 months	9 months	12 months	18 months	24 months	N
Splits with pre-split SUE<=0	mean	2.85***	2.22***	0.84	-0.39	-3.34**	-4.37***	1,345
	t-stat	(4.68)	(2.87)	(0.80)	(-0.34)	(-2.52)	(-2.68)	
Splits with pre-split SUE>0	mean	3.20***	3.72***	4.78***	4.67***	1.32	0.19	4,345
	t-stat	(8.83)	(7.23)	(6.64)	(5.44)	(1.53)	(0.18)	
All	mean	3.12***	3.36***	3.84***	3.45***	0.19	-0.90	5,690
	t-stat	(10.00)	(7.77)	(6.36)	(4.87)	(0.26)	(-1.00)	

Table 8

Operational activities after stock splits

This table presents operational activities (investment, sales growth, and gross margins) in the year following stock splits. The regression is: $R\&D/Sales,\ sales\ growth,\ or\ gross\ margins_{i,t} = \beta_0 + \beta_1\, Split_{i,t-1} + \delta' X_{i,t-1} + Firm\ fixed\ effect + Year\ fixed\ effect + \varepsilon_{i,t}$, where subscript *i* and *t* denote firm and year, respectively. *Split* is a dummy equal to one if the firm has split announcement in year *t*–1. *R&D/Sales* is R&D expenses divided by sales. Sales growth is sales in year *t* minus sales in year *t*−1, divided by sales in year *t*−1. *Gross margin* is calculated as the year *t* net sales less cost of goods sold for the year, scaled by net sales. *Size* is the natural logarithm of market capitalization in millions. *Sale* is the natural logarithm of sales. *M/B* is the market-to-book ratio from Compustat, defined as the market value of assets over the book value of assets. *ROA* is return on assets, defined as operating income before depreciation divided by total assets. *Capital expenditure* is the ratio of capital expenditure to the total asset. *R&D expenses* is the natural logarithm of R&D expenses. *Leverage* is the total debt (debt in current liabilities plus long-term debt) divided by total assets. *Cash flow* is cash flow to total assets. *Tangibility* is the ratio of property, plant, and equipment to book value of total assets. The sample period is 1984-2012. All regressions control for firm and year fixed effects. Numbers in parentheses are two-way clustered standard errors by firm and year (Petersen, 2009). ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent var.	R&D/sales	Sales growth	Gross margins
	(1)	(2)	(3)
Split	-0.008***	0.054**	0.019***
	(0.002)	(0.025)	(0.004)
Size	0.054***	0.318***	-0.063***
	(0.004)	(0.018)	(0.008)
Sale	-0.102***	-0.691***	0.142***
	(0.008)	(0.032)	(0.013)
M/B	-0.018***	-0.009	0.033***
	(0.003)	(0.011)	(0.005)
ROA	-0.083***	1.136***	0.226***
	(0.024)	(0.230)	(0.055)
Capital expenditure	-0.053**	0.218	0.094
	(0.022)	(0.192)	(0.059)
R&D expenses	0.031***	0.027	-0.012*
	(0.004)	(0.018)	(0.006)
Leverage	0.000	0.256***	0.039
	(0.012)	(0.060)	(0.027)
Cash flow	-0.107***	-1.237***	0.113**
	(0.023)	(0.239)	(0.054)
Tangibility	-0.027	-0.185**	0.029
	(0.017)	(0.082)	(0.041)
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Observations	126,558	126,017	126,525
Adjusted R^2	0.770	0.131	0.620

Table 9

Changes in analyst earnings forecast dispersion around splits

This table shows the average changes in analyst earnings forecast dispersions around splits. Analyst dispersion is defined as the standard deviation of earnings forecasts scaled by the absolute value of the mean earnings forecast. For each of 6,037 stock splits (with non-missing information on the pre-split SUE), earnings forecast dispersion is first calculated over the 3, 6, 9, and 12 months before and after the split. Changes in forecast dispersion are computed as the difference in forecast dispersion before and after the split. We use earnings forecasts for the current and next three fiscal quarters (I/B/E/S forecast period indicator (FPI) = 6, 7, 8, or 9). These splits are further divided into two groups: 1,449 splits with pre-split SUE<=0 and 4,588 splits with pre-split SUE>0. We then calculate the average changes in analyst dispersion for these two groups separately. Split firms that do not have earnings forecasts issued by analysts are excluded. *N* is the number of stock splits. Numbers in parentheses are *t*-statistics based on two-sided *t*-tests. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

		Changes in analyst dispersion around splits			
		3 months	6 months	9 months	12 months
Splits with pre-split SUE<=0	mean	0.026***	0.026***	0.014*	0.003
	t-stat	(2.62)	(2.75)	(1.79)	(0.32)
	n	1,021	1,225	1,298	1,324
Splits with pre-split SUE>0	mean	0.022***	0.008**	0.013***	0.014**
	t-stat	(5.22)	(2.09)	(2.75)	(2.39)
	n	3,701	4,198	4,327	4,361
All splits	mean	0.023***	0.014***	0.013***	0.010***
	t-stat	(4.46)	(4.00)	(4.37)	(2.72)
	n	5,150	6,020	6,284	6,366

Figure 1
Distribution of stock splits by year during the period 1984-2012

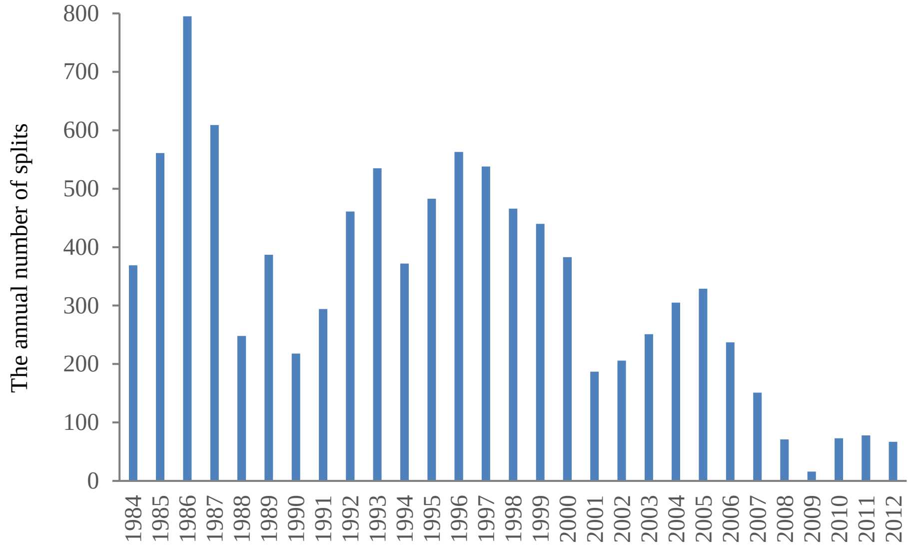

Fig. 1. This figure shows the distribution of split announcements by year from 1984 to 2012 based on our sample of 9,693 splits.

Figure 2
Post-split monthly abnormal returns

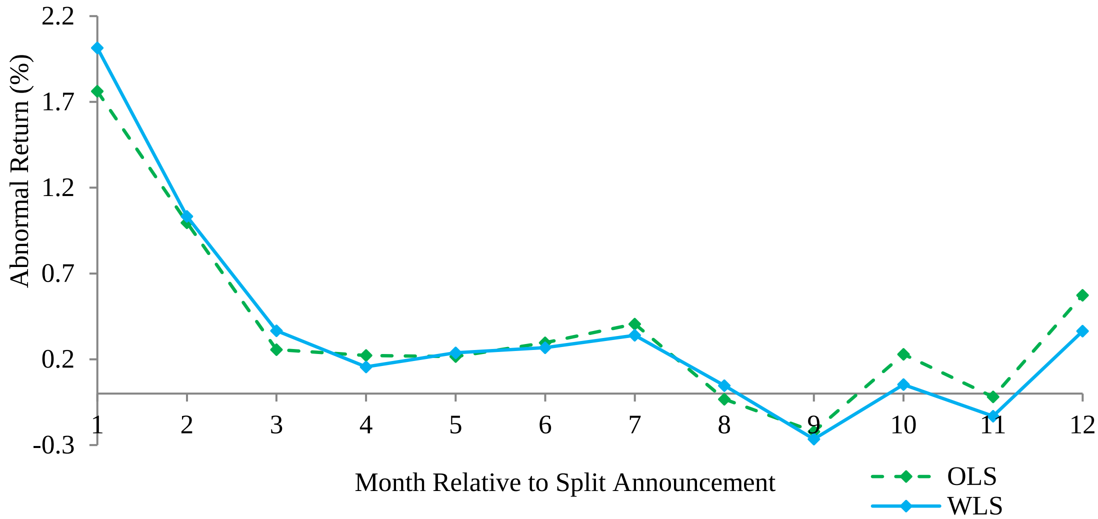

Fig. 2. This figure shows the post-split monthly abnormal returns (in %) from the 1st to the 12th month relative to the split announcement. The monthly abnormal returns are measured by the alphas in calendar-time portfolio regressions using the five-factor model. The monthly portfolio returns are equal-weighted. Both ordinary least squares (OLS) and weighted least squares (WLS) methods are used to run regressions, where the weight for WLS is the number of splits included in the portfolio in each month.

Internet Appendix for "Earnings management and post-split drift"

Table IA1
Post-split returns

This table reports the average monthly raw returns and abnormal returns (in %) in the 12 months following split announcements. The abnormal returns (alphas) are estimated using the calendar-time portfolio regression. In each calendar month, a portfolio is formed of firms that had stock split announcements in the past 12 months. We use different factor models: Fama-French's (1993) three-factor model, Carhart's (1997) four-factor model, and a five-factor model that adds the liquidity factor from Pastor and Stambaugh (2003) into the Carhart model. We compute calendar-time portfolio returns using both equal-weighted (EW) and value-weighted (VW, weighted by market value in the last month) methods. Both ordinary least squares (OLS) and weighted least squares (WLS) approaches are used to run calendar-time regressions, where the weight for WLS is the number of firms included in the portfolio in each month. Calendar months with less than 5 stocks in the portfolio are excluded from the regression. Numbers in parentheses are *t*-statistics based on Newey-West (1987) standard errors. In the last column, *Avg. stocks* is the average number of stocks in the monthly portfolio. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	OLS		WLS		
	EW	VW	EW	VW	Avg. stocks
Panel A: Sample period 1984–2012 (9,693 stock splits)					
raw return	1.44***	1.34***	1.39***	1.39***	318
	(4.32)	(4.09)	(3.81)	(4.08)	
three-factor	0.41***	0.41***	0.43***	0.42***	
	(3.45)	(3.14)	(4.08)	(3.79)	
four-factor	0.39***	0.30**	0.41***	0.26**	
	(2.95)	(1.97)	(3.32)	(2.23)	
five-factor	0.36***	0.26*	0.40***	0.22**	
	(2.62)	(1.66)	(3.25)	(2.01)	
Panel B: Sample period 1963–2012 (14,862 stock splits)					
raw return	1.48***	1.23***	1.35***	1.18***	288
	(5.51)	(4.95)	(4.45)	(4.16)	
three-factor	0.45***	0.42***	0.46***	0.44***	
	(5.72)	(4.61)	(5.63)	(4.86)	
four-factor	0.38***	0.24**	0.40***	0.23**	
	(4.05)	(2.27)	(3.91)	(2.48)	
five-factor	0.40***	0.23**	0.41***	0.22**	
	(3.75)	(1.97)	(3.96)	(2.25)	
Panel C: Sample period 1927–2012 (15,619 stock splits)					
raw return	1.38***	1.28***	1.32***	1.17***	205
	(6.20)	(6.01)	(4.59)	(4.33)	
three-factor	0.41***	0.44***	0.45***	0.42***	
	(5.75)	(4.78)	(5.78)	(4.95)	
four-factor	0.33***	0.24**	0.39***	0.22**	
	(3.91)	(2.39)	(3.90)	(2.43)	

Table IA1 (*continued*)

	OLS		WLS		
	EW	VW	EW	VW	Avg. stocks
Panel D: Sample period 1984–1997 (6,433 stock splits)					
raw return	1.74***	1.76***	1.61***	1.66***	425
	(4.20)	(5.05)	(3.58)	(4.23)	
three-factor	0.53***	0.34***	0.51***	0.32***	
	(4.91)	(2.72)	(4.65)	(2.76)	
four-factor	0.45***	0.19*	0.43***	0.22*	
	(4.28)	(1.68)	(3.86)	(1.77)	
five-factor	0.46***	0.19	0.43***	0.21*	
	(4.28)	(1.63)	(3.85)	(1.69)	
Panel E: Sample period 1998–2012 (3,260 stock splits)					
raw return	1.13**	1.00**	0.96*	0.85*	202
	(2.24)	(2.03)	(1.84)	(1.81)	
three-factor	0.37**	0.43**	0.45**	0.51**	
	(1.98)	(1.98)	(2.02)	(2.51)	
four-factor	0.35*	0.35	0.45*	0.34*	
	(1.75)	(1.52)	(1.90)	(1.81)	
five-factor	0.28	0.29	0.36	0.27	
	(1.30)	(1.16)	(1.47)	(1.36)	

Table IA2

Three-month BHAR following earnings announcements: Two-way sorts by split and SUE

This table shows the average three-month BHAR (in %) following earnings announcements sorted by standardized unexpected earnings (SUE) and by whether firms make split announcements. All earnings announcements during 1984-2012 are divided into quintiles by SUE. In each SUE quintile, we classify split firms if firms announce stock splits in the three months before earnings announcements, and non-split firms otherwise. *BHAR* is calculated from day *t*+2 to *t*+63 following earnings announcements, adjusted by subtracting the returns on a benchmark portfolio matched with size, B/M, and momentum (Daniel, Grinblatt, Titman, and Wermers, 1997). Each split firm is matched with a non-split firm in the same SUE quintile and with the closest size, B/M, momentum (prior 11-month cumulative return from month –12 to –2) to the split firm at the previous month end before the earnings announcement. Panel A reports the average BHAR for different subsamples as well as the full sample. *High – Low* shows the difference in BHAR between the highest and lowest SUE quintiles. Panel B shows the difference in BHAR between split and non-split firms for each SUE quintile and also for all the firms across the five quintiles. *N* is the number of quarterly earnings announcements. Numbers in parentheses are *t*-statistics based on two-sided *t*-tests. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

Panel A: Average three-month BHAR following earnings announcements

		SUE						
		1(Low)	2	3	4	5(High)	All	High – Low
Split firms								
	mean	1.36**	-0.04	0.66	1.89***	2.69***	1.11***	1.33
	t-stat	(2.20)	(-0.06)	(1.52)	(3.25)	(3.18)	(4.19)	(1.27)
	n	725	911	2,060	1,207	537	5,440	
All non-split firms								
	mean	-2.69***	-1.38***	-0.83***	0.01	1.11***	-0.73***	3.80***
	t-stat	(-22.17)	(-16.23)	(-10.81)	(0.10)	(9.69)	(-16.58)	(22.77)
	n	51,896	38,830	63,447	51,411	52,084	257,668	
Matched non-split firms								
	mean	-1.63**	-1.21**	-0.44	0.15	2.12**	-0.34	3.75***
	t-stat	(-2.51)	(-2.13)	(-0.88)	(0.27)	(2.31)	(-1.25)	(3.34)
	n	725	911	2,060	1,207	537	5,440	
Full sample								
	mean	-2.63***	-1.35***	-0.78***	0.05	1.12***	-0.69***	3.75***
	t-stat	(-21.96)	(-15.98)	(-10.35)	(0.64)	(9.90)	(-15.92)	(22.76)
	n	52,621	39,741	65,507	52,618	52,621	263,108	

Panel B: Difference in BHAR

Split firms – All non-split firms								
	mean	4.05***	1.34**	1.49***	1.88***	1.58*	1.84***	
	t-stat	(6.42)	(2.00)	(3.36)	(3.21)	(1.86)	(6.84)	
Split firms – Matched non-split firms								
	mean	2.99***	1.17	1.10*	1.74**	0.58	1.45***	
	t-stat	(3.33)	(1.34)	(1.66)	(2.18)	(0.46)	(3.81)	
Split firms/High SUE – All non-split firms/Low SUE								5.38***
								(6.29)
Split firms/High SUE – Matched non-split firms/Low SUE								4.32***
								(4.05)

Table IA3
Fama-MacBeth cross-sectional regressions

This table shows the Fama-MacBeth monthly cross-sectional regressions of stock returns over the period 1984-2012. The dependent variable is the monthly stock return. *Split3* equals 1 if the firm makes a split announcement in the past three months. *SUE* is in the most recent quarter. We use five SUE quintile dummies. The dummy *SUE_quintile1* (*SUE_quintile5*) is for the lowest (highest) SUE quintile. *Size* is natural logarithm of the market value at month $t-1$. *B/M* is natural logarithm of the book value of equity divided by market value of equity in the previous year. *Momentum* is prior 11-month return from month t–12 to t–2. *Reversal* is the stock return in month t–1. *Illiquidity* is Amihud's (2002) illiquidity measure defined as the previous one-year average ratio of the daily absolute return to its dollar trading volume (scaled by 10^5). *Idio. vol* is idiosyncratic volatility, defined as standard deviation of residuals from regressions of the firm's daily returns on the Fama-French three factors in the previous year. *Gross profitability* is revenues minus cost of goods sold, scaled by total assets. Numbers in parentheses are Newey-West (1987) standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
Split3	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)
Split3 × SUE_quintile1			0.009***
			(0.003)
Split3 × SUE_quintile2			-0.003
			(0.003)
Split3 × SUE_quintile3			0.002
			(0.003)
Split3 × SUE_quintile4			0.002
			(0.003)
Split3 × SUE_quintile5			-0.003
			(0.005)
SUE_quintile1		-0.023***	-0.023***
		(0.001)	(0.001)
SUE_quintile2		-0.014***	-0.014***
		(0.001)	(0.001)
SUE_quintile3		-0.004***	-0.004***
		(0.000)	(0.000)
SUE_quintile4		0.004***	0.004***
		(0.000)	(0.000)
SUE_quintile5		0.014***	0.014***
		(0.001)	(0.001)
SUE quintile rank	0.009***		
	(0.000)		
Size	-0.001**	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
B/M	0.002**	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Momentum	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)
Reversal	-0.044***	-0.043***	-0.043***
	(0.005)	(0.005)	(0.005)
Illiquidity	0.002	0.002	0.001
	(0.004)	(0.004)	(0.004)
Idio. vol	-0.243***	-0.247***	-0.247***
	(0.086)	(0.084)	(0.084)
Gross profitability	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)
Observations	883,877	883,877	883,877
Avg. adjusted R^2	0.075	0.075	0.075

Table IA4

Post-split abnormal returns by different horizons using q-factor model

This table reports post-split abnormal returns (in %) over different investment horizons based on a sample of 9,626 stock splits during 1984-2011. The abnormal returns (alphas) are estimated using a q-factor model consisting of the market factor, size factor, investment factor, and return-on-equity factor as in Hou, Xue and Zhang (2015). We form a calendar-time portfolio by including firms that had stock split announcements in the past 3, 6, or 12 months (Panel A) or firms that made split announcements in the *x*th (where *x* takes a value from 1 to 12) month before (Panel B). Monthly portfolio returns are either equal-weighted (EW) or value-weighted (VW). Both ordinary least squares (OLS) and weighted least squares (WLS) methods are used to run regressions, where the weight for WLS is the number of splits included in the portfolio in each month. Calendar months with less than 5 stocks in the portfolio are excluded from the regression. Numbers in parentheses are *t*-statistics based on Newey-West (1987) standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	OLS				WLS			
	EW		VW		EW		VW	
Horizon/ Event month	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat
Panel A: *By different investment horizons*								
(+1, +3)	1.22***	(6.02)	0.69***	(2.68)	1.51***	(7.15)	0.83***	(3.19)
(+1, +6)	0.74***	(4.31)	0.34	(1.64)	0.95***	(7.07)	0.57***	(2.81)
(+1, +12)	0.57***	(4.23)	0.38***	(2.84)	0.60***	(3.91)	0.41***	(3.39)
Panel B: *By event months*								
1	2.14***	(6.74)	0.94***	(2.97)	2.64***	(6.91)	1.24***	(3.57)
2	0.98***	(4.15)	0.99***	(3.18)	1.15***	(5.57)	1.11***	(3.59)
3	0.54**	(2.29)	0.40	(1.26)	0.74***	(2.93)	0.39	(1.30)
4	0.42**	(2.41)	-0.04	(-0.16)	0.34**	(2.00)	-0.03	(-0.13)
5	0.51***	(2.70)	0.79**	(2.16)	0.54***	(3.03)	0.77***	(2.68)
6	0.49***	(3.07)	0.71**	(2.21)	0.46***	(3.09)	0.59**	(2.02)
7	0.53**	(2.36)	0.62**	(2.21)	0.56***	(3.15)	0.62**	(2.26)
8	0.07	(0.31)	0.24	(0.76)	0.18	(0.83)	0.40*	(1.68)
9	0.02	(0.12)	0.36	(1.39)	-0.07	(-0.31)	0.39*	(1.82)
10	0.24	(0.83)	0.55*	(1.83)	0.27	(0.74)	0.52*	(1.89)
11	0.19	(0.65)	0.05	(0.17)	0.06	(0.22)	-0.30	(-1.26)
12	0.84**	(2.57)	0.94**	(2.52)	0.70*	(1.78)	0.56**	(2.21)