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Market Sentiment and Stock Splits: Differential Impacts in High and Low Sentiment Regimes

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This study investigates the impact of stock split events on abnormal stock returns, identifying significant effects in both the short- and long-term. Our findings demonstrate that market sentiment plays a crucial role, with abnormal returns being more pronounced during periods of high sentiment. This research offers two key contributions: it underscores the importance of market sentiment in shaping stock price reactions to corporate events and provides evidence supporting the signalling hypothesis, indicating that management may use stock splits to convey positive information, particularly in high sentiment environments. These insights are valuable for both investors and corporate managers when considering the implications of stock splits.

Keywords: Stock split, market sentiment

1. Introduction

Previous studies have documented well the impact of stock splits on stock prices. Most find significant abnormal returns around the split announcement dates (see, for example, Grinblatt, Masulis, and Titman, 1984; Lakonishok and Lev, 1987). Others observe abnormal returns over the mid-term or long-term following split events (see, for example, Ikenberry and Ramnath, 2002). Traditional finance theories imply that these price changes result from the release of new information (Fama et al., 1969). The abnormal returns observed upon split announcements, therefore, suggest that stock splits convey information to the market.

One group of researchers believes that management uses splits to release information to the market (signalling hypothesis). Grinblatt, Masulis, and Titman (1984) argue that underpriced firms use splits to attract analysts' attention, increasing the likelihood of a price reassessment. Conversely, overpriced firms may avoid splits as their prices are expected to decline to rational levels. Lakonishok and Lev (1987) find that firms announcing splits tend to have better operating and market performance, indicating that managers with favourable information about their firms are more likely to split stocks.

This signalling benefit is more pronounced for small firms, as information about large firms is generally more accessible.

Ikenberry and Ramnath (2002) report significantly positive abnormal returns over a year following stock splits, suggesting that investors and analysts underreact to the firms' fundamental information, leading to better after-the-split long-term performance. Additionally, Brennan and Copeland (1988) and Brennan and Hughes (1991) posit that the size of the split factor signals information.

Another hypothesis, the optimal price range hypothesis, suggests that there is a price range within which investors can trade stocks comfortably. Management should split stocks when prices are too high and reverse split when prices are too low to maintain this optimal range. Ikenberry, Rankine, and Stice (1996) find that stock splits are related to past performance and typically occur when stock prices are high. The optimal range hypothesis predicts higher trading volumes post-split, but empirical results do not support this expectation (see, for example, Lakonishok and Lev, 1987; Arbel and Swanson, 1993). Some other studies (see, for example, Angel, 1997; Schultz, 2000) suggest that splits are motivated to adjust the relative tick size to an optimal range.

In this study, we confirm that both short-term and long-term abnormal returns exist around stock split events, indicating that splits carry information about the stock's future performance.

We also examine the impact of market sentiment on stock splits. Previous studies document that market sentiment significantly influences stock performance and price (e.g., Baker and Wurgler, 2006; Hilliard, Narayanasamy, and Zhang, 2020) and that investors interpret signals differently in high and low sentiment periods. Kim and Byun (2010) find that short-term abnormal returns around split events are positively related to market sentiment, though this effect diminishes in the long term. Mian and Sankaraguruswamy (2012) and Soak et al. (2019) report that abnormal returns are more sensitive to good news in high sentiment periods and bad news during low sentiment periods. We confirm that short-term and long-term abnormal returns exist around the stock split events and that such abnormal returns are positively related to market sentiment. Furthermore, we find that abnormal returns react differently in high and low sentiment regimes, with the sentiment effect concentrated in high sentiment periods.

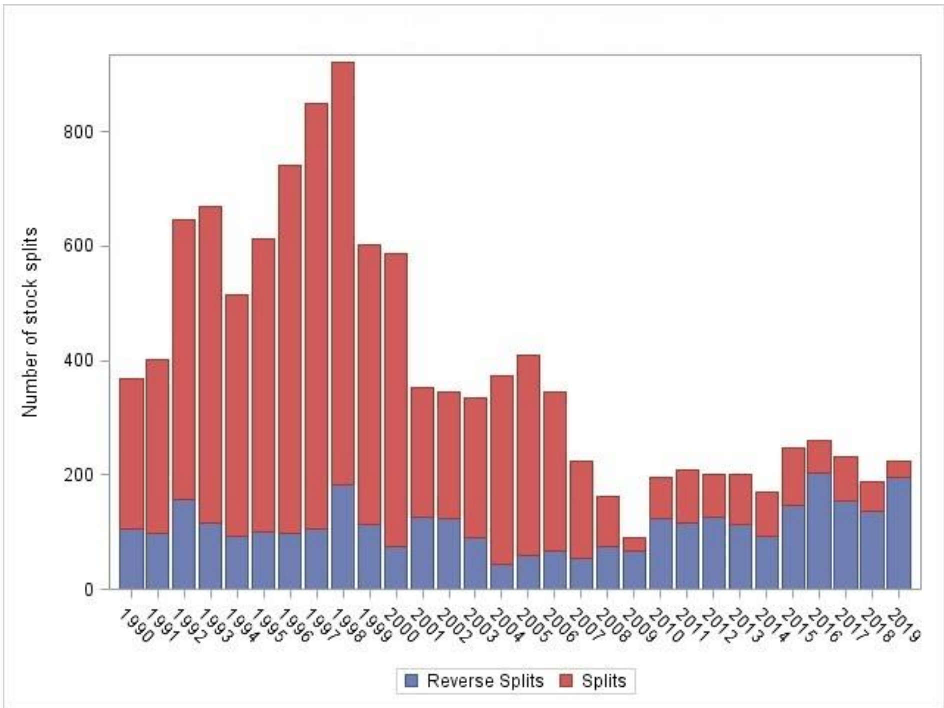
The rest of the paper is organized as follows: Section 2 introduces the data, Section 3 investigates the informational role of stock splits, Section 4 discusses the impact of market sentiment on stock splits, Section 5 examines sentiment effects in high and low sentiment regimes, Section 6 presents the robustness of the main results, and Section 7 concludes the paper.

2. Sample and Data

Our sample is primarily constructed from CRSP, covering the period from 1990 to 2019. We identify 11,678 split events using the distribution code (DISTCD) in CRSP. Figure 1 shows the annual number of split events, revealing a decline post-2000 with a slight resurgence from 2015, driven mainly by reverse splits. Out of 11,678 split events, 7,336 have announcement dates (DCLRDT), so our sample includes only these events. Most reverse splits lack valid announcement dates, leaving only 16 reverse splits in the main sample.

Firm-specific information comes from COMPUSTAT. Market sentiment is measured by the put-call ratio of SPY, an inverse indicator of sentiment, with data sourced from Bloomberg.

Figure 1: Number of stock splits per year from 1990 to 2019



3. Informational Role of Stock Splits

If a split event includes material information about the firm, we should observe abnormal stock returns around the event. We test this hypothesis by constructing cumulative abnormal returns (CAR) over three-day (t-1 to t+1), 30-day (t-1 to t+28), and 180-day (t-1 to t+178) windows around the split announcements:

$$CAR_{i,t} = \prod_{k=t-1}^{t+1}(1 + r_{i,k}) - \prod_{k=t-1}^{t+1}(1 + r_{market,k}). \quad (1)$$

The market may not be a good benchmark because many other factors may also contribute to the abnormal cumulative returns. To address this concern, we find a benchmark non-split firm for each split firm in our sample using propensity score matching (PSM[1]). Then, we use this "non-split" benchmark to estimate the abnormal return as

$$CAR_{i,t}^{*} = \prod_{k=t-1}^{t+1} \left(1 + r_{i,k}\right) - \prod_{k=t-1}^{t+1} \left(1 + r_{i,k}^{benchmark}\right). \tag{2}$$

Table 1 (Panel A) reports CARs of 3.05%, 6.67%, and 9.61% over the market for short-term, mid-term, and long-term, respectively. CARs over "non-split" benchmarks are 2.91%, 6.34%, and 8.10%, all significant at the 1% level.

Table 1: Abnormal cumulative returns around split events

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This table reports the cumulative abnormal returns around split events. We use a three-day window, a 30-day window, and a 180-day window to calculate the cumulative returns for short-term, mid-term, and long-term, respectively. The market is the S&P 500 (including dividends). A benchmark is a matched non-split firm for a split firm using Propensity Score Matching (footnote 1). The cumulative abnormal returns are calculated using equations (1) and (2). Average returns and p-values are reported.

	Return	Market	Abnormal return over market	Benchmark	Abnormal return over benchmark
Panel A: All					
(-1,1)	0.0319	0.0014	0.0305	0.0028	0.0291
	<.0001	<.0001	<.0001	<.0001	<.0001
(-1,28)	0.0792	0.0125	0.0667	0.0158	0.0634
	<.0001	<.0001	<.0001	<.0001	<.0001
(-1,178)	0.1767	0.0806	0.0961	0.0957	0.0810
	<.0001	<.0001	<.0001	<.0001	<.0001
Panel B: Splits					
(-1,1)	0.0320	0.0014	0.0306	0.0029	0.0291
	<.0001	<.0001	<.0001	<.0001	<.0001
(-1,28)	0.0798	0.0125	0.0673	0.0158	0.0639
	<.0001	<.0001	<.0001	<.0001	<.0001
(-1,178)	0.1774	0.0806	0.0968	0.0957	0.0817
	<.0001	<.0001	<.0001	<.0001	<.0001
Panel C: Reverse splits					
(-1,1)	-0.0645	0.0010	-0.0655	-0.0179	-0.0466
	<.0001	0.2839	<.0001	<.0001	<.0001
(-1,28)	-0.2115	0.0063	-0.2178	-0.0094	-0.2020
	<.0001	<.0001	<.0001	0.8054	<.0001
(-1,178)	-0.1842	0.0523	-0.2364	0.0899	-0.2740
	<.0001	<.0001	<.0001	<.0001	<.0001

Panels B and C report CARs separately for split and reverse split groups. We find significant positive CARs for the split group and significant negative CARs for the reverse split group. For reverse splits, CARs over the market are -6.55%, -21.78%, and -23.64%, and over benchmarks are -4.66%, -20.2%, and -27.4%, all statistically significant. The results indicate that while investors view splits as positive news, they view reverse splits

[1] We use size, asset turnover, profit margin, and ROA as control variables to find the predicted values of a logit model,

$$Logit(having\_split\_event_{i,t} = 1) = \alpha_{i,t} + \beta_1 Size_{i,t} + \beta_2 Turnover_{i,t} + \beta_3 Margin_{i,t} + \beta_4 ROA_{i,t} + \varepsilon_{i,t}.$$

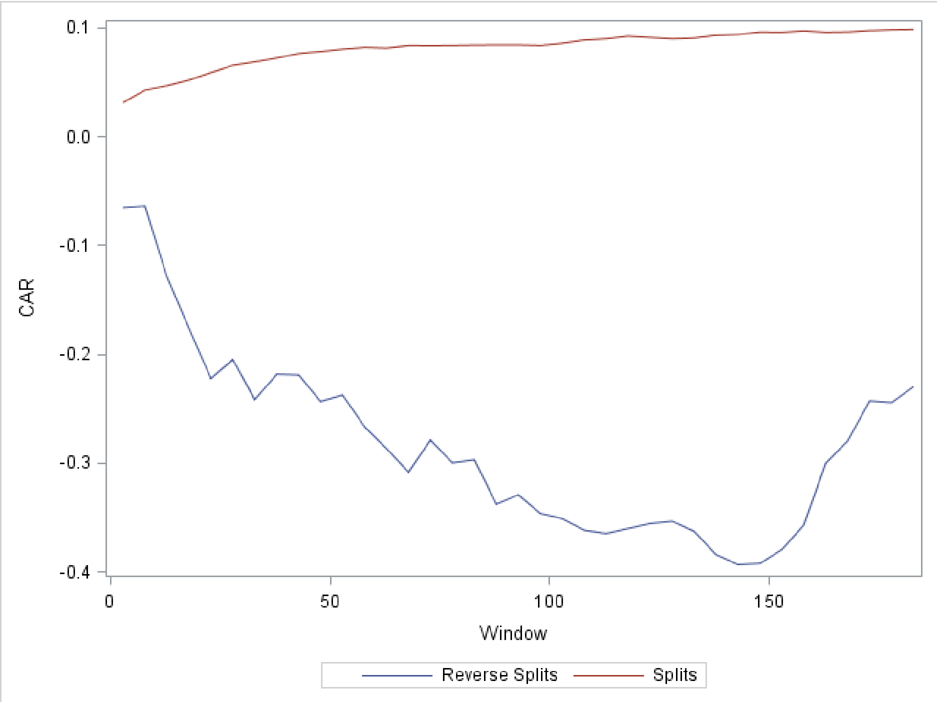
The predicted values of observations serve as scores. Then we match each split firm to a non-split firm in the same industry. The matched non-split firm is the benchmark of the split firm. We lose some sample events because of missing values during the matching process.

as negative news.

Figure 2 shows that CARs for split events increase monotonically, unlike the decline observed by Kim and Byun (2020) in a Korean sample. This implies that split firms outperform market portfolios overall. Conversely, CARs for reverse splits remain negative, indicating worse performance compared to the market.

Overall, our findings support the signalling hypothesis, suggesting that management uses splits to attract attention when possessing positive information, leading to positive abnormal returns. Reverse splits signal a lack of alternatives to boost stock prices, resulting in negative returns.

Figure 2: Cumulative Abnormal Returns in different event windows



4. The Impact of Market Sentiment

Previous studies document the impact of market sentiment on stock splits (see, for example, Kim and Byun, 2010; Kumar, Page, and Spalt, 2013). Investors tend to over-interpret market signals as market sentiment increases. Therefore, the stock splits bring higher short-term cumulative abnormal returns around the split events in a higher sentiment environment.

In this section, we investigate how sentiment affects three-day CARs around split events and the probability of future splits. We use the reciprocal put-call ratio of SPY as a sentiment measure. The put-call ratio is an indicator estimated from the options market.

It is, by nature, a forward-looking measure containing expectations about market performance. This sentiment measure is available daily and has been used in many previous studies (see, for example, Simon and Wiggins III, 2001; Vasileiou and Tzanakis, 2022). For each event, we calculate the market sentiment in the same window as we calculate the cumulative abnormal return. Equation (3) shows the calculation of market sentiment for a three-day window.

$$Sentiment_t = \frac{1}{3}\sum_{k=t-1}^{t+1} {}^{1}/_{Put\_call\ ratio_k}. \tag{3}$$

We test the impact of market sentiment on CAR using a linear model:

$$CAR_{i,t} = \alpha + \beta_1 Sentiment_t + \gamma Controls_{i,t} + FE_i + FE_t + \varepsilon, \tag{4}$$

where $CAR_{i,t}$ is the three-day CAR of a stock split by firm *i* at time t. Control variables include size, asset turnover, profit margin, ROA, and split size (Brennan and Copeland, 1988; Brennan and Hughes, 1991). The industry fixed effect and year fixed effect are also considered.

Panel A of Table 2 reports the results of the linear model. The variable of interest is $Sentiment_t$, the measure of market sentiment. All coefficients are positive [0.0299, 0.0212, and 0.0280 for models (1), (2), and (3), respectively] and significant at the 1% level. Positive coefficients indicate that the CAR is positively related to the market sentiment. These results confirm that the informational signal associated with a split event is amplified by market sentiment.

Table 2: The impact of market sentiment on stock splits

The impact of market sentiment is investigated using equations (4) and (5). Panel A reports the results of the linear regressions [equation (4)]. The dependent variable is the three-day cumulative abnormal return. Control variables include size, profit margin, ROA, and asset turnover. The industry fixed effect and year fixed effect are also taken into consideration. Market sentiment is the average reciprocal put-call ratio of SPY in the three-day window. Panel B reports the results of the probit regressions [equation (5)]. Market sentiment in Panel B is the average reciprocal put-call ratio of SPY in the previous year. Control variables are the same, but only the industry fixed effect is considered. Coefficients and p-values are reported.

	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Panel A: Linear model						
	(1)		(2)		(3)	
Intercept	-0.0162	<.0001	0.0479	<.0001	-2.2216	<.0001
Market sentiment	0.0299	<.0001	0.0212	<.0001	0.0280	<.0001
Controls	No		Yes		Yes	
Fixed effects	No		No		Yes	
N	7016		5728		5728	
Adj R^2	0.0191		0.0582		0.0639	
Panel B: Probit model						
	(4)		(5)		(6)	
Intercept	-2.7365	<.0001	-3.1927	<.0001	56.3322	<.0001
Market sentiment	0.6363	<.0001	0.7007	<.0001	0.2060	<.0001
Controls	No		Yes		Yes	
Industry fixed effect	No		No		Yes	
N	342898		233807		233807	

We also study how much market sentiment contributes to the future decision-making process of stock splits. We use a probit model [equation (5)] to investigate whether market sentiment significantly impacts the probability of stock split in the following year.

$$Probit\left(split_{i,t} = 1\right) = \alpha + \beta Sentiment_{t-1} + \gamma Controls_{i,t} + FE_i + \varepsilon. \quad (5)$$

A dummy variable $split_{i,t}$ is equal to one when firm *i* splits its stock in year t. Otherwise, it is zero. $Sentiment_{t-1}$ is the daily average put-call ratio in year t-1.

Panel B of Table 2 reports the results. The coefficients of market sentiment are 0.6363, 0.7007, and 0.2060 for models (4) to (6). All coefficients are positive and significant at the 1% level, implying that high market sentiment is associated with a higher probability of stock splits in the next year. This finding suggests that market sentiment impacts firms' decision-making process on stock splits.

5. High Sentiment Regime and Low Sentiment Regime

Previous research documents differences in investor behaviour in high and low sentiment environments (see, for example, Lee et al., 2002; Yang and Copeland, 2014; Haritha and Rishad, 2020). Investors react differently to market information in high and low sentiment environments. When the overall sentiment is high, investors react aggressively to market information. On the other hand, when sentiment is low, investors behave more rationally. Therefore, we expect that investors may interpret informational signals released from the split events differently in different sentiment environments.

We classify split events as occurring in high or low sentiment regimes based on whether sentiment is above or below the median of all split events. Panel A of Table 3 reports the test results. The coefficient of market sentiment in the high sentiment regime is 0.0387 and significant at the 1% level. The coefficient of market sentiment in the low sentiment regime is much lower (0.0151) and no longer significant even at the 5% level. The results indicate that investors react differently in high and low sentiment regimes, with their behaviour in high sentiment regimes driving the sentiment effect on split returns.

Panels B and C confirm these findings using alternative classification methods of high and low sentiment regimes, indicating robust results.

Table 3: The impact of sentiment on stock splits in high sentiment regime and low sentiment regime

We investigate the impact of sentiment in the high sentiment regime and low sentiment regime separately using the same linear model specification [equations (4)]. We divide the sample into high and low sentiment regimes based on the median sentiment. An event is classified as a high (low) sentiment event if its sentiment, the average reciprocal put-call ratio of the three-day window, is higher (lower) than the median sentiment. Control variables include size, profit margin, ROA, and asset turnover. The industry fixed effect and year fixed effect are taken into consideration. Coefficients and p-values are reported.

	High Sentiment			Low Sentiment	
	Coefficient	P-value		Coefficient	P-value
Panel A: Median of all events as cutoff					
Intercept	-1.3975	0.1296		-1.6504	0.0001
Market sentiment	0.0387	<.0001		0.0151	0.0706
Controls	Yes			Yes	
Fixed effects	Yes			Yes	
N	2930			2798	
Adj R^2	0.0768			0.0696	
Panel B: Medians of all events in each year as cutoffs					
Intercept	-2.3732	<.0001		-1.5688	0.0017
Market sentiment	0.0303	<.0001		0.0150	0.0035
Controls	Yes			Yes	
Fixed effects	Yes			Yes	
N	2917			2811	
Adj R^2	0.0702			0.0437	
Panel C: Medians of all days in each year as cutoffs					
Intercept	-2.5303	<.0001		-1.4955	0.0054
Market sentiment	0.0315	<.0001		0.0162	0.0039
Controls	Yes			Yes	
Fixed effects	Yes			Yes	
N	3254			2474	
Adj R^2	0.0692			0.0453	

6. Robustness Checks

6.1 Potential Bias Introduced by the Sentiment Effect on Stock Returns

To address potential bias arising from the effect of sentiment on the type of firms that are undergoing the split, we use the "non-split" benchmark firms as a control group. One or two benchmark firms are matched to one split firm using PSM. We also modify our models to include interaction terms capturing the effect of market sentiment:

$$CAR_{i,t} = \alpha + \beta_1 + \beta_2 D_{i,t}^{Split} + \beta_3 D_{i,t}^{Split} Sentiment_t + \gamma Controls_{i,t} + FE_i + FE_t + \varepsilon. \quad (6)$$

The β_3 coefficient captures whether the effect of stock splits on abnormal returns varies with different levels of market sentiment. Table 4 reports the test results using the "non-split" benchmarks as a control group. We find that the interaction term is positive and significant in both panels, while the coefficient on the sentiment itself loses its significance. In addition, we find that the interaction coefficient is significant only in the high sentiment regime. These findings confirm that sentiment has a significant effect on CARs after the split and that this effect is concentrated only in split firms during the high sentiment regime.

Table 4: The impacts of sentiment on stock split using matched benchmarks as a control group

We use matched benchmarks as the control group to capture the true effects of sentiment on stock splits [equation (6)]. We use Propensity Score Matching to find one or two non-split benchmark firms for each split firm. A benchmark event is a benchmark's pseudo-event that happens at the same time as the split event. The sample includes the original split sample and the benchmark pool. D is a dummy indicating whether the observation is a split stock event or a benchmark event. The dependent variable is the three-day cumulative abnormal return. Control variables include size, profit margin, ROA, and asset turnover. The industry fixed effect and year fixed effect are taken into consideration. Panel A reports the 1:1 matching results, and Panel B reports the 1:2 matching results. The 1:2 matching method matches two non-split benchmark firms to each split firm based on the propensity scores. Some split firms share benchmark firms, and the benchmark firms do not repeat themselves in the sample. Coefficients and p-values are reported.

	All		High		Low	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Panel A: 1:1 Matching						
Intercept	-1.3543	<.0001	-1.4832	0.0004	-1.0065	0.0056
D	-0.0106	0.1099	-0.0105	0.3616	0.0119	0.2263
Sentiment	0.0032	0.3376	0.0033	0.5418	0.0081	0.1438
Sentiment*D	0.0240	<.0001	0.0256	<.0001	0.0058	0.3937
Controls	Yes		Yes		Yes	
Fixed effects						
N	9231		4673		4558	
Adj R^2	0.0814		0.1013		0.0533	
Panel B: 1:2 Matching						
Intercept	-1.3722	<.0001	-1.3448	0.0014	-1.3612	0.0006
D	-0.0037	0.4760	-0.0093	0.2764	0.0183	0.0203
Sentiment	0.0065	0.0033	0.0035	0.2974	0.0131	0.0005
Sentiment*D	0.0220	<.0001	0.0265	<.0001	0.0049	0.3643
Controls	Yes		Yes		Yes	
Fixed effects						
N	12552		6366		6186	
Adj R^2	0.0763		0.0945		0.05	

6.2 Survivorship Bias

The dataset from CRSP includes some events without announcement dates. Specifically, 4,342 split events lack announcement dates, accounting for 37.18% of all events. We have excluded these events in our data formation process, as detailed in previous sections. However, the remaining events with announcement dates, referred to as "survivors," might share characteristics that influence our findings. To address this potential bias, we apply the Heckman correction to our linear models. We construct inverse Mills ratios (IMRs) for the observations in our sample using equations (7) and (8), and then incorporate the IMRs into the linear models [equations (4) and (6)]:

$$Probit\left(Having\_annoucment_{i,t} = 1\right) = \alpha + \gamma Controls_{i,t} + \varepsilon, \tag{7}$$

$$IMR_{i,t} = \frac{\phi\left(Predicted\ value_{i,t}\right)}{\Phi\left(Predicted\ value_{i,t}\right)}. \tag{8}$$

Table 5 reports the results after the Heckman correction. The results show that all results are consistent with our previous findings. The coefficients of sentiment are positive and significant at the 1% level for the full sample, and the impact of sentiment is higher for high sentiment periods. These tests confirm our previous results that cumulative abnormal returns are positively related to market sentiment and that sentiment has a higher impact in the high sentiment regime.

Table 5: Heckman correction on potential sample bias

We use the Heckman correction to address concerns about potential sample bias. Our original sampling process excludes events without an announcement date (DCLRDT). We rebuild the sample by including all split events, with or without announcement dates. A benchmark event for a split event shares the same announcement date as the split event. We then estimate the inverse Mills ratio for each event [equations (7) and (8)]. The inverse Mills ratio is added to the original linear models [equations (4) and (6)]. Coefficients and p-values are reported.

	All		High		Low	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Panel A: equation (4)						
Intercept	-2.1778	<.0001	-2.4233	<.0001	-1.5043	0.0037
Sentiment	0.0290	<.0001	0.0319	<.0001	0.0157	0.0026
IMR	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
Fixed effects	Yes		Yes		Yes	
N	5387		2718		2669	
Adj R^2	0.0709		0.0782		0.044	
Panel B: equation (6)						
Intercept	-1.4639	<.0001	-1.5168	0.0002	-1.3673	0.0004
D	-0.0106	0.1094	-0.0154	0.1587	0.0153	0.1410
Sentiment	0.0036	0.2772	0.0036	0.4847	0.0117	0.0458
Sentiment*D	0.0236	<.0001	0.0278	<.0001	0.0034	0.6376
IMR	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
Fixed effects	Yes		Yes		Yes	
N	9230		4642		4558	
Adj R^2	0.0883		0.113		0.0608	

7. Conclusion

In this study, we confirm the presence of significant abnormal returns both in the short-term and long-term surrounding stock split events. Furthermore, we demonstrate that these abnormal returns are significantly influenced by market sentiment, with a more pronounced impact during periods of high sentiment.

Our findings contribute to the existing literature in two key ways: (1) They highlight the critical role of market sentiment as a driving force behind stock price reactions to corporate events such as stock splits. (2) They offer robust support for the signalling hypothesis, indicating that management leverages stock splits to convey positive information, particularly in favourable market conditions.

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