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Stock split announcements: Abnormal returns and its determinants

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Abstract

This paper studies whether there are abnormal returns around the announcement date of stock splits and the determinants that cause these abnormal returns. This is done for firms listed on the NYSE and Nasdaq for the period April 2014 through April 2018. Positive abnormal returns were found around the announcement date, which were higher for technology firms. The results also imply that firms use stock splits to lower their stock price in an optimal trading range. No evidence is found in support of the signaling and attention hypothesis.

Keywords --- Announcement, Event study, Stock split

Contents

1. Introduction

Firms that experience a significant stock price increase rarely haven't at least once split their stocks in their lifetime (So and Tse, 2002). Even though a stock split may just seem as a purely cosmetic operation, since it has no direct effect on the value or earnings of the firm[1], the announcement of it is usually paired with a positive reaction from the market (Grinblatt, Masulis and Titman, 1984; Menéndez and Gómez-Ansón, 2003; Titman, Wei and Zhao, 2016). Previous studies have given multiple explanations for the existence of abnormal returns around the announcement date. Lakonishok and Lev (1987) found that firms use stock splits to lower their stock price in an optimal trading range, which increases shareholder liquidity. Another reason might be that firms use stock splits as a signaling tool to release favorable information to the market (Fama, Fisher, Jensen and Roll, 1969; Grinblatt et al., 1984).

The goal of this paper is to investigate if there are any abnormal returns around the announcement date of a stock split. Cross-sectional regression analysis will be used in order to investigate which determinants affect potential abnormal returns around the announcement date. The sample for this research consists of firms listed on the NYSE and Nasdaq that announced a stock split from April 2014 through April 2018.

In Section 2, relevant theories, hypotheses and past findings will be discussed. Section 3 gives an overview of the data that is used and the criteria that is used to select the data. In Section 4, a detailed explanation of the methods used will be given. In section 5, the results of the daily abnormal returns, univariate and multivariate regressions will be discussed. Lastly, in Section 6, the conclusion will be provided.

[1] There are of course costs associated with stock splits like, administrative and legal costs. These costs however, don't impact shareholders.

2. Theoretical Framework

2.1 Stock split

A stock split is a corporate event where a firm divides its total number of shares outstanding into multiple shares. The market capitalization and the existing shareholders' ownership of the firm will remain the same. The split factor is calculated by dividing the total number of outstanding post-split stocks by the amount of pre-split stocks. In order to be qualified as a stock split, the split factor has to be at least 1.25. That is, for every 4 stocks, shareholders will receive 5 stocks. Splits with a split factor below 1.25 are considered as stock dividend, since the consequences from an accounting perspective are different from stock splits.

2.2 Event study

An event study is a statistical method to measure the effect of a corporate event on the value of a firm. It also gives insight whether the market has processed the information of the event efficiently. It is often stated (Van der Sar, 2015) that Fama et al. (1696) were the originators of the event study. They studied how stock returns adjust to information that is contained in a stock split. In their paper, they proposed a new event study method to compute cumulative abnormal returns. Since then, their method has been used to study a variety of corporate events like mergers, new stock issues and stock redemptions (Mandelker, 1974; Asquith and Mullins, 1986; Dann 1980).

In order to compute cumulative abnormal returns, normal returns have to be computed first. Normal returns are estimates of the stock returns around the event date, which are deducted from the real returns in order to compute the abnormal returns. Over the years, several models have been used to compute normal returns. The market model and the constant mean return model are one of the most commonly used models to calculate normal returns (Mackinlay, 1997). The constant mean return model assumes that the mean return of an asset is constant over time. Even though this model is probably the simplest, it can yield comparable results to more complicated models (Brown and Warner, 1985). The market model assumes that the return of an asset is constant and linearly related to the return of a market index. Mackinlay (1997) argues that the market model is an improvement over other models like the constant mean return model, because the part of the return that is correlated to the market return is removed. This makes the variance of the abnormal returns lower, which increases its capability of detecting effects related to the event.

2.3 hypotheses

2.3.1 Signaling hypothesis

The signaling hypothesis states that managers make use of stock splits to release private favorable information about the value of the firm. Additionally, it is used to reduce uncertainty regarding the earnings prospects. (Fama et al., 1969). However, signals can only be considered as credible if there are costs associated, such as a decrease in reputation, with signaling false information (Grinblatt et al., 1984). According to Heikel (1984), firms want to maintain a high reputation in order to be credible when they release favorable information in the future. (Grinblatt et al., 1984) also guessed that managers wouldn't implement a stock split if they had unfavorable information, because the stock prices would fall the moment that information becomes public.

Another point to bear in mind is that stock splits are often announced after periods of continuous growth in stock price and earnings (Fama et al., 1969). An announcement of a stock split could then be seen as a signal that this growth has a permanent nature (Lakonishok and Lev, 1987).

McNichols and Dravid (1990) tested whether the split factor can be seen as a signal of managers' optimism. However, the split factor itself can't be used as a proxy for optimism, since the split factor might be influenced by the stock price and the market capitalization of the firm. They found that split factors are positively correlated with earning forecast errors after controlling for the pre-split price and market capitalization. They also found that the split factor is correlated with the announcement return after controlling for earnings forecast errors. They suggested that either the split factor is a signal for a different variable or that the signaling hypothesis is lacking.

2.3.2 Attention hypothesis

The attention hypothesis states that the announcement effect of small firms will be larger than larger firms (Grinblatt et al., 1984). Since small firms generally get less coverage from financial analysts (Atiase, 1980), less information is known about smaller firms. A stock split announcement results therefore in a relatively higher interest in smaller firms compared to larger firms. This results in higher stock returns for smaller firms. Brennan and Hughes (1991) confirmed that smaller firms indeed get more coverage by financial analysts after a stock split announcement.

Another idea regarding the attention hypothesis is that stocks of small firms aren't priced efficiently, since less information is known about them. The information that small firms release through a stock split is therefore probably not already incorporated in the stock price (Brennan and Copeland, 1988). The increased attention of small firms will result in a more efficiently priced stock, which causes the stock price to rise more than large firms. Ikenbarry, Rankine and Stice (1996) have found a significant return difference of 9.03% between small and large firms. Desai and Jain (1997) also found an inverse relationship between size and announcement returns.

2.3.3 Trading range hypothesis

The trading range hypothesis states that a stock split is announced in order to keep the stock price within an optimal trading range (Lakonishok and Lev, 1987). Small investors have namely trouble buying stocks in round lots if the stock prices are too high. Contrary, wealthy investors and institutional investors prefer high priced stocks, since they'll save brokerage costs due to the smaller weight of the fixed per-share transaction costs (Travlos, Trigeorgis and Vafeas, 2015). Shifting the stock price to the optimal trading range should therefore increase liquidity, which may explain the positive announcement effect. (Lakonishok and Lev, 1987).

McNichols and Dravid (1990) have also found results in line with the trading range hypothesis. They found that there is a significant positive relation between the pre-split price and the split factor. This indicates that firms choose their split factor with an optimal trading range in mind. So and Tse (2000) also found that firms split when a certain threshold is reached. However, they discovered that some firms split because it is the norm. There aren't actually many firms that didn't split their shares at some point in time. Firms that haven't split their shares yet, will eventually follow suit (when a certain threshold is reached) and announce a stock split. When researching the Spanish market, Menéndez and Gómez-Ansón (2003) found that the optimal trading range hypothesis prevailed over the other hypotheses.

2.4.1 Stock split effect on returns

Even though a stock split doesn't change the value or earnings of the firm, the stock market usually has a positive reaction on the announcement of a stock split.
Grinblatt et al. (1984) found a total positive abnormal return of 3.3% on pure stock splits on the announcement day and the day after. Ikenbarry et al. (1996) found a five-day announcement return of 3,38%. The paper from Titman et al. (2016) shows that there are still positive abnormal returns around the announcement of more recent stock splits in the US and China.

Most of the aforementioned researches have shown that the announcement effect is not just limited to the announcement day itself, but actually spread over multiple days. Though, these (and future) findings can't confirm that there is inside information or a delayed reaction by the market. The event date usually gets identified by looking at the publication date in a journal. This makes it hard to determine when the announcement has reached the market, since a firm may announce a stock split after the market has been closed. The spread of the announcement effect may therefore just be attributed to event-date uncertainty. (van der Sar, 2015)

2.4.2 Effect of other variables on returns

Lakonishok, Schleifer and Vishny (1994) suggested that the book-to-market (b/m) ratio should proxy for the degree of undervaluation. Ikenbarry et al. (1996) argued that if a stock split is used as a sign of undervaluation, the announcement effect should be positively correlated with the b/m ratio. Past research has shown that high book-to-market firms (undervalued firms) indeed observe a higher stock price increase during a stock split announcement then firms that are likely to be overvalued (low b/m) (Ikenbarry et al, 1996; Tawatnuntachai and D'Mello, 2002). Since the price-to-book ratio is the inverse of the book-to-market ratio, it is expected to have a negative relationship with the announcement returns.

Grinblatt et al. (1984) used a runup variable in their cross-sectional analysis, which measures the price increase in the period before the stock split. They a significant inverse relationship between the abnormal returns and the runup variable. They expected this, since the price increase in the runup period should proxy for the unreleased favorable information that is already incorporated in the price by the market.

Beladi, Chao and Hu (2016) examined whether there is a January effect in the excessive returns of stock split announcements. They found that the abnormal returns of announcements in January are higher compared to other months. They also found that firms are more likely to split their shares in January.

To this day, studies that examine the differences in announcement effect across industries are quite rare. Nadig (2015) however, found that IT firms in India that declare a stock split, create significant value to their shareholders. This has not been done for firms in the US yet.

3. Data

3.1 Data description

The necessary data for this research is obtained from two databases: Fidelity Investments and Bloomberg. Fidelity Investments is an investment company which provides news and data about corporate events that happened in North America. Information about stock splits that happened in North America from April 1st, 2014 through April 1st, 2018 are obtained from their database. This information includes the announcement day and the split ratio[2].

For the selection of the sample, the following selection criteria will be used:

- The split factor is higher than or equal to 1.25
- The firm is listed on the New York Stock Exchange (NYSE) or Nasdaq
- No other stock split or reverse split is announced within the research period (170 trading days before the announcement date until 10 days after the announcement date)

The sample consists of 123 firms after applying the selection criteria. For these 123 firms, additional financial data for the cross-sectional analysis is obtained from Bloomberg. This includes the market capitalization, price-to-book ratio, industry, trading volume and the daily closing prices. The daily closing price of the S&P-500 index is also obtained from Bloomberg. The returns (R_t) are calculated using the daily closing prices (P_t) with the following formula:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

The market capitalization and price-to-book ratios are taken from the year before the stock split is announced. The trading volume is measured by taking the 30-day average before the stock split announcement. For some firms however, there wasn't sufficient

[2]Fidelity Investments collects data from Thomson Reuters. The data is complete; it contains all stock split announcements. However, not all announcement dates were accurate. Therefore, the announcement dates were compared with the dates in Bloomberg. If there was a difference, the date from Bloomberg was used.

data to conduct a cross-sectional analysis. Those firms have therefore been removed from the sample. The final sample size consists of 119 firms.

3.2 Descriptive statistics

The summary statistics of the variables are presented in Table 1. From table 1 we see that the average market capitalization of all firms is almost 14 billion. There is a difference between market capitalizations in the NYSE and Nasdaq, however it isn't significant. The average price-to-book ratio is 6,8 which is relatively large. Judging from the standard deviation and the median, this number should be caused by some outliers. The market and firm return volatility have a standard deviation of 0,26 and 0,72 respectively. In comparison to the other variables, these two variables have a much smaller spread. The only significant difference between the NYSE and Nasdaq is the number of firms in the technology industry, namely 14 for Nasdaq versus 3 for the NYSE. This clearly shows the higher amount of technology firms present in Nasdaq. The difference between the amount of stock splits between the NYSE and Nasdaq isn't tested. Appendix A shows the distribution of announcements per day and month.

Table 1
Summary statistics and comparison NYSE and Nasdaq

Panel a: summary statistics full sample

	N	Mean	Standard deviation	Median
Market Cap. (in millions)	119	13.890	44.592	2.817
Price-to-book	119	6,80	17,77	3,50
Trading Volume (in thousands)	119	1.859	5946	446
Runup Firms (%)	119	11,68	14,31	9,35
Pre-split price	119	96,17	114,55	73,21
Market Return Volatility (%)	119	0,71	0,26	0,70326
Firm Return Volatility (%)	119	1,61	0,72	1,43242

Panel b: Comparison NYSE and Nasdaq

	NYSE	Nasdaq	p-value
Stock Splits	48	71	
Technology firms	3	14	0,025*
January Split	5	6	0,724
Market Cap (in millions)	15.750	12.634	0.669
Price-to-book	7,08	6,61	0,869
Trading Volume (in thousands)	1891	1838	0,956
Pre-split price	103,5824	91,16	0,507

** Significant at 5% level*

Table 2 reports the correlation coefficients of all independent variables and their corresponding p-values. The strongest correlation is the one between market capitalization and trading volume with a coefficient of 0,95. The split factor is highly correlated with three variables: market capitalization, trading volume and the pre-split price. This is particularly interesting for the regression on the split factor. Another notable relationship is the one between the runup and firm return volatility. The coefficient of 0,65 implies that there is a strong linear relationship between the total returns in the runup period and the volatility of the returns in that same period.

Table 2
Correlation matrix and significance level of all independent variables

Variable		1	2	3	4	5	6	7	8	9	10
1	Market Cap.	1									
2	Price-to-book	0,00	1								
3	Volume	0,95*	0,01	1							
4	Runup	-0,12	-0,03	-0,05	1						
5	Pre-split Price	0,44*	0,07	0,47*	0,03	1					
6	Technology	0,25*	0,25	0,29*	0,15	0,16	1				
7	Market std.	0,05	0,01	0,05	0,11	-0,04	0,07	1			
8	Firm std.	-0,10	-0,02	-0,04	0,65*	-0,07	0,19*	0,29*	1		
9	January split	0,12	-0,03	0,05	0,02	-0,05	0,04	-0,08	-0,07	1	
10	Split Factor	0,50*	0,03	0,60*	0,07	0,65*	0,19*	0,07	0,09	0,00	1

** significant at 5% level*

4. Methodology

4.1 Event Study

Measuring the effect of stock split announcements will be done by using an event study. In this paper, the event study will be as follows: The announcement day of the stock split will be t=0. The control period ranges from t=-170 to t=-71. During this period, the stock returns shouldn't be affected by the event. It is therefore possible to make an estimation of α and β, which will be used to calculate normal returns. In addition to the control period, a runup period will be used, which ranges from t=-70 to t=-11. This period will be used to calculate additional variables. The test period ranges from t=-10 to t=-11 in order to capture any effect related to the stock split announcement.

In order to measure possible abnormal returns during the test period, the realized returns (R_{it}) have to be compared to the normal returns (R^*_{it}). The normal returns will be calculated using the market model, where the total return index of the S&P-500 will be used as the market return. Before the normal returns can be calculated, the α and β of the market model have to be estimated. The estimation can be done by performing the following regression for the control period:

$$R_{it} = a_i + b_i R_{MIt} + u_{it} \tag{2}$$

The estimated a and b from equation (1) will be used in a regression to calculate the normal returns for the test period.

$$R^*_{it} = \hat{a}_i + \hat{b}_i R_{MIt} \tag{3}$$

When R^*_{it} is calculated, the abnormal returns can be calculated by subtracting equation (3) from (2).

$$ar_{it} = R_{it} - R^*_{it} \tag{4}$$

ar_{it} shows how much the realized return of stock *i* in period *t* differs from its expected result under regular conditions. All the individual abnormal returns will be combined in average abnormal return, in order to make a valid judgment of the effect of the announcement on the return.

$$AR_t = \frac{1}{N}\sum_{i=1}^{N} ar_{it} \qquad (5)$$

The significance of AR_t will be determined by using a t-test. In order to calculate the test statistic, the standard deviation is necessary. However, since the standard deviation is typically unknown, it is common to use an estimator s_t (Van der Sar, 2015). The t-value can then be calculated by substituting the square root of equation (6) for the standard deviation in equation (7).

$$s_t^2 = \frac{1}{N-1}\sum_{i=1}^{N}(ar_{it} - AR_t)^2 \qquad (6)$$

$$TAR_t = \frac{AR_t}{s_t/\sqrt{N}} \qquad (7)$$

4.2 Variables

As stated before, the runup period will be used to create a couple of extra variables that will be used in the regressions. For every firm, a variable will be created that measures the run up of the stock returns for the runup period, RUF. The run up is measured by calculating the buy-and-hold return for the runup period. With this variable it is possible to see the extent to which the stock price trend in the prior period influence has on abnormal returns. There are also two variables created that measure the volatility of the stock returns and the market (STD_Firm and STD_Market). These variables act as a proxy regarding the consensus of the stock price.

The last variable that will be created is the residual split factor, RSF. In order to make the split factor a viable signaling variable, the part of the split factor is needed that is not caused by the pre-split stock price and market capitalization of the firm. Therefore, the same approach as McNichols and Dravid (1990) will be taken, by regressing the pre-split price and the market capitalization on the split factor. However, since the trading volume has a high correlation with the split factor (table 2), it will also be used in another regression. The residuals of this regression (8) will be stored in the variable RSF.

$$SplitFactor_i = a_i + \beta_1 PRESPLIT_i + \beta_2 MARKETCAP_i + \beta_3 VOLUME_i + \varepsilon_i \qquad (8)$$

4.3 Regressions

With the use of an event study it is possible research if there are days where abnormal returns are present. The cause of these abnormal returns can be examined with the use cross-sectional regression analysis. The dependent variable will be the cumulative abnormal returns (CAR). The amount of days that will be used to calculate the CAR will be determined by the days where the abnormal return is statistically significant. However, if a day is significant that is relatively far away from the announcement day (e.g. day 5), it is most likely a coincidence and will therefore not be included in the CAR.

When the CAR is determined, univariate regressions will be performed on the CAR with all the variables. That is, the run-up variables, residual split factor (RSF), log of market capitalization (MARKETCAP), log of trading volume (VOLUME), pre-split price (PRESPLIT), price-to-book ratio (PTB), JAN and TECH. JAN is a dummy variable which takes the value 1 if the split was announced in January and 0 if the split is announced in the remaining months. TECH is also a dummy variable which takes the value 1 if the industry in which the firm operates is the technology industry. It takes the value 0 if the firm operates in all other industries.

The statistically significant variables will determine which variables will be used in the multivariate regression. However, if a variable is close to being significant in the univariate regression, it will also be added to see if it becomes significant in the multivariate regression.

5. Results

5.1 Daily abnormal returns

Table 3 reports daily abnormal returns around the announcement date for the complete sample. On day 0, daily abnormal returns amount to 0,52%, which are statistically significant at the 5% level (T=2,57). The abnormal returns on day 0 are positive for 56,3% of the splitting firms. The only other day with statistically significant abnormal returns is on day 1. On that day, daily abnormal returns amount to 0,60%, which are significant at the 1% level (T=2,68). The makes the cumulative abnormal returns (the announcement effect) over the event window (0, +1) amount to 1.12%. Appendix B depicts the cumulative abnormal returns over the complete test period. It illustrates the jump in returns around the two-day announcement period very well.

Table 3
Daily abnormal returns around the stock split announcement dates

Days	Abnormal Returns (%)	Percentage of positive (%)	T-statistic	Cumulative abnormal returns (%)
-10	-0,03	47,06	-0,20	-0,03
-9	-0,40	40,34	-1,22	-0,43
-8	0,05	47,90	0,26	-0,38
-7	-0,22	48,74	-1,19	-0,60
-6	-0,17	51,26	-0,82	-0,77
-5	0,01	53,78	0,08	-0,76
-4	-0,01	48,74	-0,07	-0,77
-3	0,08	52,10	0,53	-0,69
-2	0,06	47,90	0,44	-0,63
-1	0,07	44,54	0,55	-0,56
0	0,52	56,30	2,57**	-0,04
1	0,60	63,03	2,68***	0,56
2	0,15	50,42	0,92	0,71
3	0,25	44,54	0,91	0,96
4	0,18	57,14	0,97	1,14
5	0,04	48,74	0,31	1,18
6	-0,01	48,74	-0,05	1,17
7	0,11	52,94	0,62	1,28
8	0,07	50,42	0,40	1,35
9	-0,13	42,86	-0,77	1,22
10	-0,12	47,06	-0,95	1,10

** Significant at 10% level   ** Significant at 5% level   *** Significant at 1% level*

5.2 Split factor regression

Table 4 reports the results of the regression analysis on the split factor. Regression (1) shows that the market capitalization variable is positive, but not significant (t=1,16). PRESPLIT also has a positive relationship with the split factor and it is significant at the 1% level (t=7,50). Regression (1) contains the same variables as the regression from McNichols and Dravid (1990). Regression (2) has the trading volume as an additional explanatory variable. From this regression it becomes clear that VOLUME is positive and significant at the 1% level. PRESPLIT is still positive and significant at the 1% level. MARKETCAP is still significant at the 5% level, but now the coefficient is negative. Since the coefficients and the R^2 changed substantially in regression (2), regression (1) clearly suffered from omitted variable bias.

Table 4
Multivariate regressions on split factor (t-values in parentheses)

Variable	Regression (1)	Regression (2)
MARKETCAP	0,047	-0,262***
	(1,16)	(-3,37)
PRESPLIT	0,005***	0,005***
	(7,50)	(8,22)
VOLUME		0,291***
		(4,55)
Constant	1,282***	0,035
	(4,18)	(0,09)
Adjusted R^2	0,4142	0,4993

** Significant at 10% level* *** Significant at 5% level* **** Significant at 1% level*

5.3 Cross-sectional univariate regression analysis

Table 5 reports the results of the univariate regressions. It shows that the variables regarding the attention hypothesis (MARKETCAP, VOLUME) aren't significant at the 5% level. MARKETCAP, however, is significant at the 10% level (t=1,66). The coefficients of the signaling hypothesis (PTB, RSF) are both positive but rather small and insignificant (t=0,69; t=0,73). This is also the case for PRESPLIT (t=1,37). RUF and STD_Firm are both insignificant (t <1,96). STD_Market has a coefficient of 2,679 and is significant at the 5% level (t=2,36). This implies that if the volatility of the market increases with 1 percentage point, the announcement returns increase with approximately 2,68%.

If the announcement happened in January, it doesn't have any significant effect on the announcement returns, since the t-value of JAN is -0,12. Lastly, TECH has a coefficient of 0,0218 and is significant at the 1% level (t=2,64). This means that if a firm operates in the technology industry, its announcement effect increases with 2,18%.

Table 5
Determinants of the cumulative abnormal returns on event window [0, +1]
(univariate regressions).

Variable	Coefficient (t-value)	Constant (t-value)	Adjusted R^2
MARKETCAP	0,0026*	-0,0093	0,0145
	(1,66)	(-0,73)	
PTB	0,0001	0,0105***	-0,0044
	(0,69)	(3,28)	
VOLUME	0,0017	-0,0105	0,0054
	(1,28)	(-0,61)	
RUF	0,0027	0,0111***	-0,0085
	(0,899)	(2,86)	
PRESPLIT	0,0000	0,0078**	0,0074
	(1,37)	(2,02)	
RSF	0,0032	0,0112***	-0,0040
	(0,73)	(3,78)	
STD_Firm	-0,0294	0,0119	-0,0086
	(-0,07)	(1,59)	
STD_Market	2,6970**	-0,0080	0,0372
	(2,36)	(-0,92)	
JAN	-0,0012	0,0114***	-0,0084
	(-0,12)	(3,63)	
TECH	0,0218***	0,0081**	0,0480
	(2,64)	(2,60)	

5.3 Cross-sectional multivariate regression analysis

Table 6 reports the results of the multivariate regressions. Regression (1) includes all variables from the univariate regressions that were at least significant at the 10% level. The results show that the coefficients of STD_Market and TECH are still positive. TECH is still significant at the 5% level, however STD_Market is now only significant at the 10% level. MARKETCAP hasn't become significant at the 5% level within the multivariate regression. In fact, it is not significant anymore at all.

By removing the market capitalization variable, we get regression (2). In this regression STD_Market and TECH are both positive and significant at the 5% level again (t=2.23; t=2.52). The coefficient of 2,4964 indicates that if the market volatility in the runup period increases with 1 percentage point, the announcement effect increases by approximately 2,5%. Firms operating in the technology industry experience an average announcement effect increase by 2.05%.

Table 6
Determinants of the cumulative abnormal returns on event window [0, +1]
(multivariate regressions)

Variable	Regression (1)	Regression (2)
STD_Market	2,4454*	2,4964**
	(2,19)	(2,23)
TECH	0,0196**	0,0205**
	(2,40)	(2,52)
MARKETCAP	0,0022	
	(1,43)	
Constant	-0,0261*	-0,0095
	(-1,81)	(-1,12)
Adjusted R^2	0,0873	0,0791

** Significant at 10% level* *** Significant at 5% level* **** Significant at 1% level*

6. Conclusion

This paper investigates whether abnormal returns around the announcement date of stock splits can be achieved. The determinants of the abnormal returns are also examined. This is done for firms listed on the NYSE and Nasdaq for the period April 2014 through April 2018.

It has become clear that the market still positively reacts to stock splits announced between 2014 and 2018, which is in line findings in past research for different periods and markets (Grinblatt et al., 1984; Fama et al., 1969; Titman et al., 2016; McNichols and Dravid, 1990; Menéndez and Gómez-Ansón, 2003). The fact that the announcement effect is spread out over two days might be explained by a delayed reaction by the market. However, it is more likely that it is caused by uncertainty regarding the event-date, since stock splits could be announced after the market has closed.

The results show some evidence regarding the trading range hypothesis, since the split factor is positively correlated with the pre-split price. This indicates that firms indeed make use of stock splits in order to lower the price within an optimal range. It is therefore likely that this has an effect on the announcement returns. These results are in line with findings from McNichols and Dravid (1990).

Contrary to past research, no evidence has been found regarding the signaling hypothesis. The insignificance of the residual split factor implies that firms do not choose their split factor to release private favorable information to the market. The market also doesn't see a stock split as a signal of undervaluation. The results also didn't show evidence that supports the attention hypothesis, since the market capitalization and trading volume didn't have a significant effect.

The results also showed that the market volatility has a positive effect. This implies that if the consensus of the market price was low, the average announcement effect of a firm increases. The results also showed that firms operating in the technology industry, have a larger announcement effect. There is however no clear explanation for this finding. This effect might as well be caused due to a limited sample size of technology firms.

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Appendix A: Distribution of stock splits

Table 7

Distribution of stock split announcements by day and month

Panel a: Distribution by day (N=119)	
Day	**Number of firms announced**
Monday	14
Tuesday	23
Wednesday	35
Thursday	29
Friday	18
Panel b: Distribution by month (N=119)	
Month	**Number of firms announced**
January	11
February	11
March	8
April	16
May	11
June	4
July	9
August	15
September	3
October	13
November	8
December	10

Appendix B: Cumulative abnormal returns around the announcement date

Figure 1

Cumulative abnormal returns plotted over the complete test period