The determinants of abnormal returns during stock splits

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Enok Gartvall, Carl Landahl

Abstract:

This thesis studies how stock splits on the Nasdaq Composite Index between 2001-2019 affect the abnormal returns around the announcement day. Furthermore, it also examines which factors may explain the abnormal returns. Four hypotheses are constructed and then tested by using an event study and a regression model. The result from the event study shows significant abnormal returns of 2.24% in a 7-days period, and 2.64% in a 11-days period. The results also suggest that liquidity has a significant negative effect on the abnormal return for firms with low market value. This implies that US firms of low liquidity, high levels of asymmetric information, and low market value have higher positive abnormal returns around the stock splits than those firms of high liquidity, low levels of asymmetric information, and high market value. Thus suggesting that liquidity can proxy information asymmetry. The results, however, show no support for the effect of split factors on the abnormal returns.

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1. Introduction

In this section, the topic of the research is introduced and problematized. The background, purpose, hypotheses and the outline for this thesis will also be presented.

1.1 Background and problem discussion

Over the spectrum of research in finance, academics have tried to figure out the motives behind stock splits. A stock split is a way to increase the number of shares in the market and put downward pressure on the price, without restructuring the cashflow or the market value of the firm and the stockholder's ownership. Since stock splits do not change the fundamental value of the firm, such events are to be considered as cosmetic strategies for the firm (Brennan and Copeland,1988)

However, in July 2020, Apple announced a 4 to 1 stock split, which means that each existing shareholder received 3 new shares per 1 existing. 2 weeks later, Tesla also announced a stock split but with a 5 to 1 ratio. Both shares gained significantly after the announcements, with Tesla returning over 70% in the 20 consecutive days of the announcement and Apple returning over 30% (Reuters, 2020). Although these cases are extreme, the relationship between stock splits and abnormal returns are a far-reaching and well-documented phenomenon.

During the years of research in stock splits, different theories have emerged which contradict that stock splits are to be seen only as a cosmetic strategy. The fundamental contradiction is based on the fact that firms that announce a stock split can earn excess returns, and that there are therefore other incentives that firms can benefit from (Fama et al., 1969). Excess returns refer to the return that cannot be explained by the market and are defined as abnormal returns (MacKinlay, 1997).

There seem to be several reasons for the occurrence of abnormal returns during stock splits. In the literature, there are mainly 3 theories that seem to explain the anomaly that occurs in stock splits. These are the signalling hypothesis, the trading range hypothesis and the liquidity hypothesis. First, the signal hypothesis implies that the firm's management holds positive private information which is signalled at the announcement of a stock split and hence the

share is priced up. The trading range hypothesis suggests that there is an optimal price level for a share, and hence the size of the stock split is controlled by the desired level of the firm's management. The optimal level entails a cost-effective way of buying shares, which provides higher liquidity and a broader ownership structure. The liquidity theory suggests that firms undergo a stock split to increase the liquidity of the stock. This is done by lower prices being considered more attractive, which increases market activity for the stock. (McNichols & Dravid, 1990; Grinblatt et al., 1984; Copeland, 1979; Fama et al., 1969).

Previous research on the subject suggests that abnormal returns can be earned during a stock split. One of the pioneers in the research of stock splits, Fama et al. (1969) show that the abnormal return on stock splits can be explained through increased future dividends. Dividends are generated by positive results, which means that the stock market will revalue the stock price to the level where future dividends are discounted

Apart from the explanation of whether abnormal returns are a result of future dividends, McNichols & Dravid (1990) show that the abnormal returns differ depending on the size of the stock split. In practice, this means that a firm that announces a larger stock split than another can expect higher returns.

As discussed here, there are a number of different explanations and theories for the anomaly of a stock split, and even though this is a field that has been researched over a long period, there are still unanswered questions. This allows for a further investigation in form of this thesis. The approach will be to include a few previously tested factors, but also new ones to test if it is possible to find other significant explanations for the abnormal returns and in this way broaden the understanding of the phenomenon of stock splits.

1.2 Purpose and hypotheses

The purpose of this thesis is to study how stock splits on the Nasdaq Composite Index between 2001-2019 affect abnormal returns around the announcement day. Furthermore, it aims to test which factors could explain the abnormal returns, in particular the effect and implications of stock liquidity. This thesis will test the following hypothesises:

Hypothesis 1: *Stock split announcements result in abnormal returns.*

Hypothesis 2*: There is a negative relationship between liquidity and abnormal returns at stock split announcements.*

Hypothesis 3*: Liquidity before stock split announcements can be used as a factor for proxying information asymmetry.*

Hypothesis 4*: Split factors, the ratio of shares issued per existing shares, have a significant effect on abnormal returns.*

1.3 Outline

This thesis is arranged in 8 sections. The first section is the introduction, where previous research is briefly mentioned, and the hypotheses of this thesis is presented. Section 2 and 3 discuss previous research and the theoretical background that underlies this thesis. Section 4 deals with the methodology of the thesis. In section 5, a presentation on the data collection will be done. Section 6 presents the empirical results of the study. The analysis is in section 7, where the results will be discussed further, and in the last part, the conclusion is presented with proposals for future studies.

2. Theoretical background

2.1 Stock split

A stock split is a corporate action in which a firm's share price changes. In practice, this means that existing shares are divided into more new shares. A firm can choose to implement a straight stock split or a reverse stock split. The difference is that in a straight stock split, a new number of shares are issued and in a reverse stock split, the number of issued shares decreases. This implies that the share price decreases and increases respectively. A stock split with a ratio of 2:1 implies that existing shareholders receive 2 new shares for 1 existing and the price of the shares should fundamentally decrease by 50%. Thus, there is no change of existing ownership in direct connection with the split (Aktiespararna, 2019).

2.2 The efficient market hypothesis

Since computers began to be used, academics have tried to predict future economic cycles through historical patterns. The most common way to predict this was by studying the stock market and its prices. Since share prices reflect a firm's wellbeing, prices should then also contain information about the economy as a whole (Bodie et al, 2011). Kendall (1953) was one of the first to study market efficiency, which infers that stock prices continuously reflect both private and public information. Kendall's (1953) study shows that stocks tend to follow a random walk, which implies that it is not possible to predict a future price based on the current information available, and the investor can therefore not earn abnormal returns. Based on Kendall's (1953) research, Fama (1970) presents the theory of market efficiency and believes that three assumptions must be met for a perfectly efficient market. These are:

(1) There are no transaction costs related to trading securities.
(2) All available information is available without cost to all market participants.
(3) All market participants agree on the implications of current information for the current price and distributions of future prices of each security.

In the real-world economy, these assumptions are not fulfilled continuously. This led Fama (1970) to divide market efficiency into three forms: *weak-form efficiency, semi-strong efficiency, and strong efficiency.*

1. Weak efficiency:

Stock market prices reflect all history and are regulated according to new historical data. This means that the price of a share reflects the historical data. The implication is thus that abnormal returns cannot be achieved through the usage of historical data (Fama, 1970).

2. Semi-strong efficiency

In addition to previous conditions on historical data, prices also reflect all new public information. Public information is exemplified as annual reports or press releases. When public information is released, the price will be adjusted accordingly. The revaluation speed of the price puts the semi-strong efficiency to test (Fama, 1970).

3. Strong efficiency

The last form of efficiency states that prices fully reflect all existing information. This implies that all historical and public information as well as private information is reflected in the price. In this strong form of efficiency, all arbitrage opportunities are completely excluded and thus also the possibility to earn abnormal returns (Fama, 1970).

McKinlay (1997), argues that the event window in an event study (discussed in *4.2*) must contain trading days before the event takes place. This is based on the assumption that some investors have access to insider information (i.e. private information) about the event. This infers that the price possibly exhibits abnormal movements before the announcement, that can be linked to the event. Hence, a semi-strong efficiency is assumed in event studies, both in general and in this study.

2.3 The signalling hypothesis

Several researchers indicate that the firm's management announce stock splits associated with increased optimism. One of the first was Fama et al. (1969) who show that there is a tendency for firms to increase their dividends after undergoing a stock split. According to the authors,

this phenomenon is based on the management's positive view on future revenues, which implies that the firm can at least maintain the same dividend policy as before the split. Furthermore, Fama et al. (1969) argue that the market is efficient since stock prices changed shortly after the announcement.

Pilotte (1997) shows in his study, based on listed firms between 1982 and 1989, that firms that carry out a stock split report increased earnings both before and after a stock split. This, according to the author, indicates that a stock split not only signals short-term optimism but also long-term. These results suggest that there is a positive correlation between the market reaction in the event of a stock split and subsequently reported firms' revenues, which supports the theory of an efficient market (Pilotte, 1997).

Ikenberry et al. (1996) show that only 3% of the firms in their study carry out a stock split when the share price is below the historic median price of the share. According to the authors, this indicates firms only choose to implement a stock split when the firm exhibits a positive trend, which implies that the market consensus is that firms choose to undergo a split when the management is optimistic about the future.

3. Previous empirical studies

3.1 Abnormal returns during stock splits

Different studies show a statistically significant positive correlation between abnormal returns and the announcement of stock splits. Fama et al. (1969) study stock splits made on the New York Stock Exchange between 1927-1959 and found a significantly abnormal return associated with stock splits, and derive this to what previously mentioned, market future expectations of cash dividends.

However, Grinblatt et al. (1984) demonstrate a positive abnormal return on equities traded on the US stock market of 4.5%, 4- 43 days after the stock split. This infers that Grinblatt et al. (1984) believe that the market is not perfectly efficient because, in the case of a stock split, firms signal optimism, and investors can earn excess returns. Furthermore, Grinblatt et al. (1984) do not support Fama et al.'s (1969) theory that prices around stock splits are corrected due to the ability to pay future dividends. This since Grinblatt et al.'s (1989) dataset, contains stocks that do not pay cash-dividends but still earn abnormal returns during the stock split. Rather, they suggest that prices are rising as a result of the firm's future cash flows.

Lakonishok & Lev (1987) provide research with further empirical results by demonstrating abnormal returns around stock splits. The authors demonstrate a return between 3 and 4 % and derive this return to an improved performance prospect. Furthermore, Ikenberry et al. (1996) confirm earlier presented research on abnormal returns associated with stock splits. The paper studied the short-term and long-term effects of a stock split, by exploring a selection of 1275 stock splits between the years 1975 to 1990. The results show that during a 5-day period around the event day, stocks tend to outperform the market by 3.38%. Furthermore, the study finds that stock splits result in an abnormal return of 7.93% in the first year after the split and 12.15% in the following 3 years. The authors present two different reasons for the presence of abnormal returns. First, in the event of a stock split, the stock is moved into an "optimal trading range", which increases the liquidity of the share, and that the split itself is used as a signal of optimism, which is consistent with the signal hypothesis.

Brennan & Copeland (1988) confirm the previous empirical results of abnormal returns associated with stock splits. Unlike the other presented studies, this includes a perspective on

transaction costs in the event of a stock split. The authors report an abnormal return of 2.9% during the two-day split announcement through a sample of 1035 stock splits between the period 1967-1976. However, the study finds that investors' transaction costs exhibit a negative correlation with the share price. As a result, a stockbroker's commission will increase in the event of a stock split, which makes the broker more inclined to recommend the stock to an investor. Besides the fact that stockbrokers are more inclined to propose a stock that has undergone a stock split, Jensen & Murphy (1990) report that the firm's management own shares in the firm they work for, through various incentive programs, where their compensation is based on the firm's performance. This would in practice make them more likely to promote and implement firm-specific activities which increase the valuation partly for the firm but also their individual compensation. All mentioned earlier empirical findings indicate a positive relationship between abnormal returns and stock splits, which will also be this thesis conjecture.

3.2 Influence of information asymmetry in abnormal returns

Ford et al. (2012) study analysts' coverage degree of influence in the event of a stock split. They report that firms covered by more analysts than others generate 1.7% lower abnormal returns over a 3-days period and that the marginal effect of stock split events is a declining function of the number of analysts covering the firm. Ford et al. (2012) explain that analysts' coverage has an inverse relationship with asymmetric information. The lower the information gap between the firm and the market, the less reaction to positive events. These results strengthen the signal hypothesis, that a firm's management will incorporate coverage of analysts not only in the event of a split but also the size of the split factor (Ford et al., 2012).

Brennan & Hughes (1991) study the relationship between investor transaction costs as a form of brokerage commissions and stock prices. The authors assume that investors will only invest in stocks they have knowledge about and where the source of information is their stockbrokers and its analysis. Furthermore, the study presents that a stock split increases a broker's incentive to do earnings forecasts because the cost of stock trading (i.e. brokerage commission) is built up from a fixed cost as well as a variable cost. In the event of a stock split, the price per share is reduced, which means that the relative cost of buying the share increases. As investors will only invest in stocks that they have knowledge about, the study

assumes that the brokerage firm is the determining factor of the information asymmetry. As a result, a split will reduce the information asymmetry (Ford et al. 2012).

The report "*Evidence that Analyst Following and Institutional Ownership Accelerate the Pricing of Future Earnings*" by Ayers & Freeman (2003) examines whether stock prices with high analyst coverage discount future profits earlier than the other firms. The research shows that firms with relatively high analyst coverage prior to an earnings announcement tend to exhibit lower price volatility and hence a lower response to new information. Furthermore, the study confirms the hypothesis that firms with high analyst coverage incorporate earnings earlier than the other firms with low coverage. The results of this study are consistent with previous results presented by Ford et al. (2012).

Arbel & Swanson (1993) study the role of information in the share price during the announcement day of a corporate event. The selection is based on 105 US stocks between the period January 1, 1984, and December 31, 1987. The results show that the degree of market expectation on the day of the announcement is related to the size of available information, where the richness of information is measured by using analyst coverage as a proxy. In addition, the authors present that the magnitude of the message effect during day 0 to +1 is greater for firms that exhibit low levels of information, which supports earlier reported results.

The parallel between liquidity and initiation of analyst coverage has earlier been investigated by Roulstone (2003). The results show that liquidity increases as a result of the initiation of analyst coverage. This implies that analyst coverage can proxy for the transfer of information to the market and thus decrease the information asymmetry.

3.3 Influence of split factors on abnormal returns

McNichols & Dravid (1990) examine whether it exist a correlation between the size of the split and the management's private information about the firm's future performance. The size of the split is defined as the split factor and describes the relation between numbers of newly issued and existing shares. These results show that firms with a higher split factor tend to hold more positive private information than others resulting in greater abnormal returns. Furthermore, the authors link the theory of the split factor to the "optimal trading range

hypothesis". This implies that the firm's choice of split factor will be made to the level of the price that causes the share to fundamentally fall within the optimal level. According to the theory, the firm's management uses private information to determine the split factor, which infers that the market discounts the management's optimism and thus the firm's future performance through the size of the split factor. This phenomenon implies that the stock will be traded on a higher level in equilibrium (McNichols & Dravid, 1990).

Later studies show results in parity with McNichols & Dravid (1990). Yagüe et al. (2009) test whether the size of the split factor signals a firms' performance in the Spanish stock market. Like McNichols & Dravid (1990), Yagüe et al. (2009) report that the size of the split factor has a significant impact on abnormal returns. An extension to previous studies is made by showing that the size of the split factor has a greater impact when the split is larger than expected by the market. Furthermore, Yagüe et al. (2009) argue that a firm's management chooses unexpectedly high split factors to signal that the positive momentum is permanent and not temporary.

Conroy & Harris (1999) study the importance of the firm's stock price in a stock split. Like Yagüe et al. (2009) and McNichols & Dravid (1990), the authors present that the size of the split is a decisive factor for abnormal returns. The results indicate that when the split is larger than expected, i.e. when a stock is split more times than expected, the abnormal return will be up to 3.17% higher than if it's in line with the market expectation. Furthermore, the authors present that the analyst's forecast earnings errors increase when the split is larger than expected, where forecast earnings errors proxies for information asymmetry. This phenomenon may explain that larger splits lead to higher abnormal returns (Conroy & Harris, 1999).

3.4 Summary of previous empirical studies

Author(s)	Published	Main focus	Conclusion
Fama et al.	1969	Stock prices reactions to new information (stock split). Test of efficiency.	The market is efficient due to upward price corrections after announcements. Only as a result of the firm's future capability to pay cash-dividend.
Grinblatt	1984	The effect of stock splits and stock dividends on both the announcement day and the ex-day.	Abnormal returns were found on both days. The motives are not optimism regarding future cash- dividends. Rather future cash flow.
Lakonishok & Lev	1987	Why firms engage in events such as stock splits or stock dividends.	Restoring stock prices to normal levels. Stock splits signalling permanent future earnings.
Ikenberry	1996	Testing both if abnormal returns can be enjoyed and if the "Signalling hypothesis" and the "trading range hypotheses are consistent.	Developing a new model called "Self-selection hypothesis" which indicates that management uses stock splits to control the price. Management only does the split if they are optimistic about the future. Displays evidence on abnormal returns.
Brennan & Copeland	1988	A cost-function approach to stock splits that might explain the anomaly.	Post-split stock prices and trading costs are closely related. Management communicates private information by issuing a stock split.
Jensen & Murphy	1990	How the compensation for top management is affected by the development of the firm.	A positive relationship between top-management and shareholder-wealth. CEO's wealth increases with USD 3.25 for every USD 1000 increase in shareholder-wealth.
Ford et al.	2012	Financial analysts' impact on the market reaction in the event of a stock split.	The market reaction in terms of abnormal return has a negative correlation with analyst coverage. The larger the asymmetric information, the greater reaction.
Brennan & Hughes	1991	Studying the effect of brokerage commission and the incentives to produce analysis on the firm in the event of stock splits.	Management will split the stock if they have favourable private information, which will amend the price. Analyst's coverage and the share price exhibits a negative correlation.
Ayers & Freeman	2003	If firms followed by analysts are discounted for future earnings earlier than the other firms.	Firms with higher analyst coverage incorporate earnings earlier than the others. During earnings releases, firms with higher coverage have a lower market response in terms of price volatility.
Arbel & Swanson	1993	The role of information during the announcement day for stock splits.	Market expectations are closely related to the size of the information the market holds on the stock. Firms that exhibit lower levels of information richness are more affected by the announcement effect.
Roulstone	2003	The relationship between liquidity and analyst coverage.	Analyst coverage exhibits a positive correlation with market liquidity.
McNichols & Dravid	1990	If the split factor signalling any information in the event of stock splits.	Management chooses their split factor based on the level of optimism that signals to the market.
Yagüe et al.	12009	Tests the "Signalling hypothesis" on splitted Spanish stocks as well as the dependence of split factors.	Stock Prices are upward revised in event of stock splits based on signals regarding future earnings. When split factors are greater than expected, the market will classify the earning signal as permanent.
Conroy & Harris	1999	Investigate the relationship between stock splits and share prices.	Managers construct the split factor to change the stock price to the desired level which is stable over time.

4. Methodology

4.1 Research approach

A quantitative method is the basis of this thesis. As mentioned in the introduction, the purpose of the study is to investigate whether abnormal returns can be found in stocks that have undergone a stock split during the period 2001-2019. To be able to perform this, statistical tests are made on a quantitative basis. Previous studies such as Grinblatt et al. (1989) are also implemented with a quantitative approach.

This thesis is not intended to create a new theory but rather to test the previously presented theories. According to Greener (2008), this is defined as a deductive approach. A deductive approach thus means that the author starts by examining previous theories and then formulates hypotheses about whether previous theories work, which is done by using data. Hence, a deductive approach is often associated with a quantitative study (Greener, 2008). In the previous studies presented, a deductive approach is most prominent.

4.2 Event studies

To test the hypothesis, the thesis relies on using an event study, where the event of interest is the announcement of the stock split. This approach aims to disentangle the effect on the stock price of a firm-specific event. This is done by estimating the normal return for a stock using a specified window of time, referred to as estimation period, and comparing this to the return of the period close to the event, referred to as event window (MacKinlay, 1997).

The idea of event studies relies on the assumption of efficient markets (discussed in part 2.2). This by comparing the normal return of the stock with the return under the event window to estimate the effect of the event, namely how the market values the information of the event. If the information provided by the event is new and considered positive, then the returns around the event are bound to exceed the normal or expected return, described in the literature as abnormal returns (Kolari & Pynnönen, 2011; Brown & Warner, 1985).

To summarize, MacKinlay (1997) describes how the implementation of an event study can be narrowed down to these steps, (formatted by Paccico et al. (2018)):

1. Definition of the Event window
2. Computation of the normal returns
    a. Definition of the estimation window
    b. Choice of the estimation model
3. Estimation of the abnormal returns
4. Statistical testing for the significance of the abnormal returns

4.2.1 Estimation period and event window

As mentioned, to perform an event study both the estimation period and the event window need to be specified. The definition of an event window is the time period that is considered acceptable for isolating the event and the range of the event window usually extends to both before and after the observed event, this to catch potential movement around the announcement date caused by, for example, insider trading (MacKinlay, 1997).

However, widening the range of the event window too much counteracts the very purpose of isolating the event. The estimation period aims to estimate the normal or expected return of the stock, to be able to calculate the excess return from the expected or the abnormal return. In determining the range of the estimation period, the upper bound day, closest to the event, is usually chosen so that the estimation period and the event window do not overlap each other. This as the effect of the event might contaminate the estimation of the normal return (MacKinlay, 1997).

The choice of the lower range for the period, (earliest observation), is through balancing the positive effect, of that a longer period contains more data on returns, and thus ought to result in a better prediction, and the negative effect of that a longer period of data may contain other events that may contaminate the estimation. An approach used is to decide for an estimation period and then exclude all observations with events in the given period to avoid contamination. However, this does heavily limit the number of observations or demands a short estimation period (MacKinlay, 1997).

The lower bound of the estimation period chosen for this study is 120 trading days before the start of the event window, which is based on MacKinlay (1997). The upper bound of the estimation window is set to 10 days prior to the start of the event window, to avoid the earlier mentioned contamination, where the event influences the normal performance parameters. Resulting in an estimation period of 115 days, ranging from 125 days before the event to 10 days before the event. MacKinlay (1997) further suggests including trading days prior to the event since there might exist leakage of price-affecting information before the announcement. This thesis will use both 3 and 5 days prior and after the event to test if there is any significant difference in abnormal returns. The time series is illustrated down below, where T is the day of the event (T=0), T = -5 is the 5 days before the event, T = +5 is the 5 days after the event day.

Figure 1. Illustration of estimation period and event window
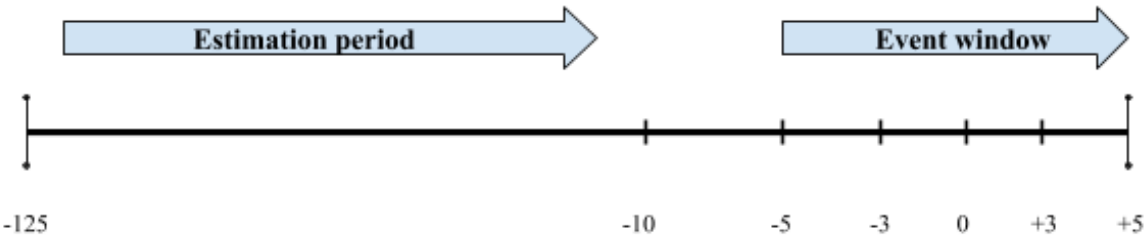
Source: Illustration by the authors

4.2.2 Normal and abnormal returns

To calculate the abnormal return, the actual/observed return is compared with the normal one. The normal return is the one that an investor can expect to receive if the event does not take place. The general formula for calculating the abnormal is therefore written as;

$AR_{iT} = R_{iT} - E(R_{iT}|X_T)$ where AR_{iT} is the abnormal return for the T_{th} period, R_{iT} is the actual return for the period and $E(R_{iT}|X_T)$ is the normal or expected return. (MacKinlay, 1997).

There are different procedures for calculating normal returns. MacKinlay (1997) presents both statistical and economic methods. The advantages of using statistical methods are that it does not depend on economic arguments and are therefore less difficult to use. In this study we use the most common one, that being the Single Index Model (Sorokina et al. (2013); MacKinlay (1997)).

Single Index Model (SIM):

$$E[R_{iT}] = \alpha_i + \beta_i R_{mT} + \varepsilon_{iT}$$

$E[R_{iT}]$ is the expected return for stock i during the period t. R_{mT} is the index return during period t and ε_{iT} is the firm-specific error term. This thesis uses the Nasdaq Composite Index daily closing prices as the approximation of the index returns. Furthermore, the Single Index Model estimates the parameters alpha (α_i) and beta (β_i) over the estimation period (MacKinlay, 1997). The estimation of the parameters enables to estimate the normal return by adjusting the market return for the given estimation day. An advantage of using this model is that it controls for the variation in index returns during the event window, which simplifies the main purpose of using event studies, namely if the event of interest affects the abnormal returns (MacKinlay, 1997). Using this model, we can then compute the abnormal return for a single day event by subtracting the normal return from the observed/expected return calculated during the event window.

$$AR_{i,T} = R_{i,T} - (\alpha_i + \beta_i R_{m,T})$$

In this study, however, the aim is to study a multi-day period. This is done by calculating the cumulative abnormal returns (CARs). Where t_1 and t_2 are the boundaries for the event window.

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t}$$

To observe the impact of events on multiple firms, the average abnormal returns (AAR) is computed. Using both measures, summing both over time and between firms, allows investigating the average effect over multiple days (Kothari & Warner, 2007).

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,T}$$

Finally, the cumulative average abnormal returns can be calculated as below:

$$CAAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AAR_t$$

4.2.3 Statistical testing of the abnormal returns

To be able to draw any conclusions and assume economic relevance from the calculated abnormal returns in the previous step, there is a need to apply statistical testing. The objective of this testing is to show that the abnormal returns are statistically significantly different from zero. Most commonly used tests in related research can be divided into the groups, parametric and non-parametric tests, the difference being that parametric assumes a particular type of distribution of return while non-parametric take no such assumption (Kolari & Pynnönen, 2010; Kothari & Warner, 2007).

Using the most basic parametric tests for this study would rely on the assumption of normally distributed abnormal returns with a mean 0, and variance of σ^2_{AR}. This implies that also *AARs, CARs,* and *CAARs* are normally distributed with mean 0 and variances σ^2_{AAR}, σ^2_{CAR}, σ^2_{CAAR}. A widely used, more fitted, parametric test regarding abnormal return is the one of Patell (1976), defined as:

$$t_p = \frac{\bar{A}\sqrt{n}}{\sqrt{(m-p-1)/(m-p-3)}} = \bar{A}\sqrt{\frac{n \times (m-p-3)}{m-p-1}}$$

Where, $\bar{A}$ is the average scaled abnormal return, n is the number of firms, p is the number of explanatory variables in the expected return regression and m is the number of observations in the estimation period. This statistical test relies on the idea to use scaled abnormal returns (SARs), defined as:

$$A_{it} = \frac{AR_{it}}{S_i\sqrt{1 + d_t}}$$

Where S_i is regression residual standard deviation, and d_t is a correction term of the form $\acute{x}_t(XX)^{-1}x_t$, with vector x_t of explanatory variables and matrix X of variables values in the estimation period.

Kolari & Pynnönen (2011) describe that the reason behind using SARs for statistical tests is standardization. It weights the individual observations by the inverse of the standard deviation, which results in that the less volatile observations increase in weight while more volatile observations get weighed down.

The downside of this test is that it does not correct for cross-sectional correlation between the abnormal returns. This might affect the results, especially in studies that observe the effect of a single event on multiple variables (Pacicco et al., 2018).

To improve the reliability of the outcome a more refined version of the parametric test is proposed by Kolari & Pynnönen (2011), defined as:

$$t_{AP} = \frac{\bar{A}\sqrt{n}}{\sqrt{(m-p-1)/(m-p-3)}\sqrt{1+(n-1)\bar{r}}}$$

Using the correction factor of, $\sqrt{1+(n-1)\bar{r}}$, to adjust for cross-correlation, where $\bar{r}$ is the average of the sample correlations of estimation period residuals (Kolari & Pynnönen, 2011). This adjusted version of Patell (1976) is the model for statistical testing that was chosen for this study. Even though this paper studies firms with specific event days, so that cross-correlation is not an immediate problem, it is still considered to be a more robust alternative that increases the reliability of the results.

4.2.4 Estudy dataset

To perform the event study, the software statistical program Stata and the prespecified commando "Estudy" (Pacicco et al. 2018, 2020) are used. This allows for an event study with firm-specific events, and through that avoid normalizing the data based on the event window. Something that would otherwise require heavy sorting of the data, and therefore be out of the scope of the timeframe for this study. This command is created to perform an event study with the possibility to customize the statistical framework and through that, the possibility to achieve more robust results.

4.3 Abnormal trading volume

Campbell & Wasley (1996) present, based on previous research conducted by Ayinkya & Jain (1989) and Cready & Ramanan (1991), an approach to calculate the abnormal trading volume. This is done initially by computing the percentage of shares outstanding out of the volume traded each day. V_{it} is the trading volume, n_{it} is the number of shares traded for stock i on period t, S_{it} is the outstanding shares for stock i on period t.

$$V_{it} = \frac{n_{it} \times 100}{S_{it}}$$

Campbell & Wasley (1996), like Ayinkya & Jain (1989) and Cready & Ramanan (1991), use logarithmic values on trading volume (assumed exponential development). To avoid distorted results, the authors have substituted 0 against 0.000255 on the days when the trading volume was zero. This because the natural logarithm is not defined for the value 0. In this thesis, however, only trading volumes > 0 are observed, which means that no action of substitution needs to be taken. Furthermore, the abnormal trading volume is estimated using the mean adjusted trading volume.

$$\bar{V}_i = \frac{1}{T} \sum_{t=f}^{t=I} V_{it}$$

$$v_{it} = V_{it} - \bar{V}_i$$

Where T is the number of days used in the estimation period, I and f are upper and lower bound trading days. However, in this model, the same number of days in the estimation period will be used when calculating abnormal returns. This improves the possibility of comparisons between them (Campbell & Wasley, 1996).

4.4 Regression model

Like several other studies such as McNichols & Dravid (1990) and Ford et al. (2012), this study will use a multifactor regression model. This because an event study only tests if abnormal returns can be found in connection to corporate action events (McKinlay, 1997).

Hence, the model will estimate whether split factors, abnormal trading volume, analyst coverage, market value, and liquidity can explain the variation of abnormal returns around stock splits. Depending on the outcome of the analysis, we will be able to reject or not reject our hypotheses. The following regression model was used to carry out the analysis,

$$CAR_i = \beta 0 + \beta 1 * (LN)LIQ + \beta 2 * (LN)MV + \beta 3 * SPL.FAC. + \beta 4 * CAL + \beta 5 * AC + \beta 6 * (LN)MV * (LN)LIQ + \varepsilon_i$$

where CAR_i is the dependent variable and measured +- 5 days from the event, LIQ is the logarithm of the normal/expected number of trades as a percentage of the number of outstanding shares for the firm measured 115 days (-125 to -10) prior to the event window. MV is the natural logarithm of the firm's market value 10 days before the event, $SPL.FAC.$ a dummy taking the value 1 for firms with split factor 1 and 0 for firms with split factor 0.5. Furthermore, CAL is the cumulative abnormal liquidity measured +- 5 days from the event, AC is the number of analysts covering the firm 10 days before the event and ε is the error term.

4.5 Variables in the regression model

4.5.1 Normal liquidity

The variable liquidity LIQ is the normal liquidity measured 115 (-125 to -10) days before the event takes place. This variable is calculated similarly to Campbell & Wasley (1996), Ayinkya & Jain (1989), and Cready & Ramanan (1991). Normal liquidity is calculated by taking the average from the trading volume. As mentioned in the presentation of abnormal trading volume above, trading volume is calculated as a percentage between the number of shares outstanding and the total daily volume. The variable for normal liquidity is interesting from the point of view that it possibly can be used as a proxy for information asymmetry. Firms that tend to have high normal liquidity before a stock split takes place, may be covered by media monitoring to a greater extent (Roulstone, 2003). As previously presented by Ford et al. (2012), market value is used as a proxy for information asymmetry and shows that firms covered by more analysts have lower asymmetric information. In a stock split which is seen as a signal of optimism, the firms with the highest information asymmetry will generate the highest abnormal return (Ford et al., 2012). This variable will test hypotheses 2 and 3.

4.5.2 Market value

In our regression model, a new variable is introduced, which is the market value of a firm. This variable is measured by the logarithmic market value 10 days ($T = -10$) prior to the split announcement, which is 5 days before the event window for the event. This is done similarly to Brennan & Copeland (1988), to test whether firm size has a significant impact on the abnormal return. The results in previously presented studies, regarding the impact of firm size on the abnormal return when announcing a stock split is that larger firms have a negative correlation with abnormal returns at stock splits, i.e. that the smaller the firm, the higher the abnormal return (Ford et al., 2012.; Brennan and Copeland, 1988).

4.5.3 Cumulative abnormal liquidity

In this thesis, the cumulative abnormal liquidity (CAL) is also used as an explanatory variable for abnormal returns. CAL is not mentioned in previously found research but should thus be seen as a form of abnormal trading volume presented by Campbell & Wasley (1996), Ayinkya & Jain (1989), and Cready & Ramanan (1991). The abnormal trading volume is the difference between the observed volume during the event window and the normal/expected volume 115 (-125 to -10) days before the event takes place. A reduced abnormal trading volume indicates that the turnover rate of shares decreases around the studied time period, in this case, a stock split. Previous research on changes in liquidity during a stock split shows a decrease. Copeland (1979) shows that liquidity, measured as trading volume, decreases after a stock split. From this, it is expected that the abnormal trading volume will decrease during a stock split. However, the unanswered question is how the change in the cumulative abnormal trading volume affects the abnormal returns.

4.5.4 Analyst coverage

The coverage of analysts' impact on abnormal returns has previously been studied by Ford et al. (2012). In this thesis, analyst coverage (AC) is also used as an explanatory variable for abnormal returns. Analyst coverage is measured as the number of analysts following the firm 10 days ($T = -10$) before the event, and 5 ($T=-5$) days before the event window. Ford et al. (2012) present a negative relationship between the number of analysts covering the firm and the abnormal returns during a stock split, implying that if a firm is covered by more analysts,

a stock split by the same firm tends to result in lower abnormal returns. This result is also the conjecture in this thesis. Furthermore, this study will proxy media monitoring by analyst coverage (i.e. number of analysts covering the firm).

4.5.5 Split factor

This thesis studies whether the split factor has a significant effect on cumulative abnormal returns. The definition is made in line with Hu et al. (2017), where the split factor is the number of newly issued shares per previous shares. In practice, this means that a stock split with ratio 2:1 has a split factor of 1 and a stock split with ratio 3:2 has a split factor of 0.5. Split ratios of 2:1 and 3:2 are the most prominent, and also the argument for the inclusion (Investopedia, 2020). Previous empirical evidence shows a positive correlation between abnormal return and split factor, which implies that a higher split factor results in higher abnormal return respectively (McNichols & Dravid, 1990).

4.6 Limitations and awareness

4.6.1 Event studies

One of the fundamental assumptions in an event study is that the market is efficient. Fama (1970) presents in his article that all public information should reflect asset prices, which creates the assumption that markets are semi-efficient (see discussion of efficient markets). In the light of previously presented research by Fama (1970), it is assumed in this thesis that the market is semi-efficient. However, some studies indicate that markets cannot be classified as effective as Fama (1970) believes, which violates the reliability of an event study. Malkiel (2003) presents in his paper several reasons why the market is not efficient. One of the basic preconditions for an efficient market is that it follows a random walk. In practice, this means that stock prices are not predictable and as a result, investors cannot earn excess returns on historical information. Based on studies done by Lo and MacKinley (1999), Malkiel (2003) presents that stock prices can follow a predictable pattern in the short run and that there is, therefore, a form of momentum in stock prices, which is considered as a violation of the Efficient Market Hypothesis (EMH). Malkiel (2003) explains this through psychological traits. When the share price rises, investors will pay attention and buy the stock, which creates a "bandwagon effect" (Malkiel, 2003).

Bowman (1983) presents the importance to isolate the effect of the event of interest. If the event of interest occurs in connection with another firm-specific announcement, the actual effect cannot be measured. The author exemplifies this through confounding events such as dividend announcements and earnings announcements. If these two events are contaminated during the event window, an event study will not be able to isolate the effect of interest (MacKinley, 1997). The solution is to tighten the event window to isolate the real effect. Therefore, MacKinley (1997) believes that event studies are a well-performing methodology for measuring changes in stock prices for new information in the short run, but less performed in the long run. This because when the time-span increases, so does also the risk that other effects will contaminate the effect of interest. In this thesis, we will try to isolate the effect of a stock split by a tightened event window, which is between -5 to +5 days.

Furthermore, MacKinlay (1997) presents other problematic aspects of an event study. One of these is the risk of sampling intervals. In practice, this means the difference in outcomes depending on whether the research uses, for example, daily, weekly, or monthly price data. Furthermore, the author believes that the best outcome occurs at short price ranges, i.e. more frequent price data. In this thesis, daily price data is used based on the argumentation made by MacKinley (1997), which reduces the risk of distorted results.

5. Data

5.1 Collection of data

The empirical analysis includes time series data of daily price and trading volume of 60 firms on the American stock exchange, Nasdaq Composite Index. The firms in the sample have all announced and implemented a stock split between 2001-01-01 and 2019-12-31. From the list of possible firms, 30 were randomly chosen with each respective split factor. The selection of the specific firms was accomplished through the usage of the Center for Research in Security Prices (CRSP) dataset**.**

Data over historic daily prices, trading volume, shares outstanding, market value, and analyst coverage were then collected from the Thomson Reuters Eikon database for each firm and then downloaded to the statistical program STATA. In total, CRSP provided information on 2101 stock splits made on Nasdaq Composite between 2001-01-01 to 2019-12-31.

5.1.1 Data criteria

For the sample to be representative of this study, several data criteria were formed. The fundamental criterion was that there should be complete information about the firms. Complete information is classified as the date for both the announcement and the ex-day is available and that there are daily stock prices and volumes for the entire period. Furthermore, firms were specified to have a stock adjustment factor of 0.5 or 1, implying a 3:2 split or 2:1 split, and a share code of 10 or 11, implying an ordinary common share. This means that all other types of securities (e.g. preference shares & derivatives) are excluded. Shares outstanding were also decisive to compute the abnormal trading volume in accordance with Campbell & Wasley (1996). Based on these criteria, a total of 1206 observations were removed and 895 left. From these 895 observations, 466 observations with split factors of 1 and 429 observations with split factors of 0.5 were identified. 30 firms with a split factor of 0.5 and 30 firms with split factor 1 were chosen randomly.

List of data criteria:

1. *Announcement day can be identified.*
2. *Ex-day can be identified.*
3. *Split factors can be identified.*
4. *Daily stock prices 125 days prior to the event and 5 days after the event*
5. *Daily volume 125 days prior to the event and 5 days after the event.*
6. *Shares outstanding six days prior to the announcement.*

Table 1 – Selection of data

	Removed Observations	Remaining observations
Total Observations	*0*	*2101*
Incomplete information on announcement day or ex-day	*-128*	*1973*
Incorrect split factors	*-1078*	*895*

Source: Illustration by the authors.

5.2 Data sources

The essential source for obtaining information about stock splits has been made through the Center for Research in Security Prices (CRSP). This allows for the identification of stock splits that occurred between 2001-01-01 to 2019-12-31 on the U.S stock exchange, Nasdaq Composite Index. CRSP tool for data management allows for the specification of the desired data. To achieve the purpose of this thesis, the share type is specified with identification codes 10 and 11, which are defined as common shares. Furthermore, split factors are specified to 1 and 0.5, which allows for grouping the data and thus a comparison between the groups.

After the information was retrieved from CRSP, the Thomson Reuters Eikon was used to retrieve historical daily stock closing prices, volumes as well as Nasdaq Composite Index closing prices for the specified time period. When acquiring outstanding shares, numbers of

analysts covering the firms, and market value, the Data Item Browser (DIB) function, which is available in advanced search on the Thomson Reuters Eikon, was used.

Both sources of information retrieval are considered reliable. CRSP currently has approximately 500 academic institutions as users, spread over 35 countries, and is classified as one of the leading organizations in data collection for security prices (CRSP, 2020). Thomson Reuters is also widely used by academics, employees in the financial industry, and news media around the world. According to Reuters itself, up to 1 billion people worldwide interact daily with Reuters services (Thomson Reuters, 2020).

6. Results

6.1 Descriptive statistics

Table 2 displays descriptive statistics for the 60 included observations in this study, giving an overview of the factors included in the regression models. More specifically, it displays the number of observations, the mean, the standard deviation, the minimum, and the maximum values for the variables Market Value, Analyst coverage, Cumulative abnormal liquidity, Cumulative abnormal returns, and Liquidity.

Table 2 – Descriptive statistics

Variable	Observations	Mean	Standard Dev.	Min.	Max.
Cum. Abnormal Ret. (CAR)	60	2.287	8.354	-26.333	24.671
(Ln) Market Value	60	21.366	1.749	18.69	26.424
Analyst Coverage (AC)	60	10.133	9.518	0	36
Cum. Abnormal Liq. (CAL)	60	3.332	8.705	-22.217	42.793
(Ln) Liquidity	60	-0.389	0.983	-2.560	1.557

Source: Illustration by the authors and data from Thomson Reuters Eikon.

Table 3 demonstrates the correlation between the variables included in the regression analysis. This is done to examine the presence of multicollinearity. According to Alin (2010), multicollinearity is the linear relationship between 2 or more constituent variables. Multicollinearity is a statistical problem that creates a lack of reliability for the model because the independent variables cannot measure the marginal effect (Alin, 2010).

As Table 3 shows, there are no statistically significant correlations between the independent variables and the dependent variable, cumulative abnormal return. The statistically significant results are between the independent variables, analyst coverage & market value, logarithmic average trading volume & analyst coverage, and between split factor & market value. Notably is the high level of correlation of 78.57% between analyst coverage and market value, implying that, as the market value increases, so will analyst coverage, which is in line with

Ford et al. (2012). One explanation for the considerably high correlation is that institutional investors (pension funds etc) have liquidity requirements for investments. Assuming that institutional investors usually buy analysis from the brokerage firms. Hence, giving incentives for the brokerage firms to make analyses of liquid stocks based on their main target customers' liquidity requirements.

Table 3 – Correlation matrix

Variable	Cum. Abnormal Ret. (CAR)	Analyst Coverage (AC)	Cum. Abnormal Liq. (CAL)	(Ln) Market Value	(Ln) Liquidity	Split Factor
Cum. Abnormal Ret. (CAR)	*1*	-	-	-	-	-
Analyst Coverage (AC)	*-0.151* *(1.00)*	*1*	-	-	-	-
Cum. Abnormal Liq. (CAL)	*-0.155* *(1.00)*	*-0.0140* *(1.00)*	*1*	-	-	-
(Ln) Market Value	*-0.0720* *(1.000)*	*0.7857**** *(0.000)*	*-0.0221* *(1.000)*	*1*	-	-
(Ln) Liquidity	*-0.0490* *(1.00)*	*0.428*** *(0.01)*	*0.261* *(0.655)*	*0.3230* *(0.177)*	*1*	-
Split Factor	*0.0243* *(1.00)*	*0.219* *(1.00)*	*-0.0131* *(1.00)*	*0.4394**** *(0.007)*	*0.201* *(1.00)*	*1*

Notes: P-values in parenthesis. *p < 0.1; **p < .05; ***p < .01.

Source: Illustration by the authors and data from Thomson Reuters Eikon.

6.2 Estimated models and core results

6.2.1 Abnormal returns associated with stock splits

Table 4 displays the event study results over cumulative average abnormal return (CAAR) associated with a stock split over two different event windows, both 3 and 5 days prior and after the split. It includes all observations together and then two groups of 30 firms respectively. The inclusion of all observations shows high significance for both the event periods and results in values of approximately 2.24 % and 2.64 % respectively. These results are in line with previous research in the regard that it indicates that the announcement of a stock split generates positive abnormal returns (Grinblatt et al., 1984). Group 1 includes observations with the split factor 1 (split ratio 2:1), and Group 2 includes observations with the split factor 0.5 (split ratio 3:2). Both groups showed significant results on conventional levels ($p < 0.1$) for the two event windows, with group 1 having a CAAR of approximately

1.66 % over the 7 days event window and a CAAR of approximately 2.00 % over the 11 days event window. Group 2 exhibited a CAAR of approximately 2.81 % over the 7 days event window and a CAAR of approximately 3.26 % over the 11 days event window.

Table 4 – Event study

	CAAR [-3,3]	CAAR [-5.5]
CAAR Group All	2.2409%***	2.6413%***
	(0.0003)	(0.0005)
CAAR Group 1	1.6552%*	1.9961%**
	(0.0591)	(0.0430)
CAAR Group 2	2.8148142%***	3.2643%***
	(0.0030)	(0.0080)

Notes: P-values in parenthesis. *p < 0.1; **p < .05; ***p < .01.

Event study om multiple event dates, with 2 event windows specified, using the Patell (1976) test, with the Kolari and Pynnonen (2011) adjustment.
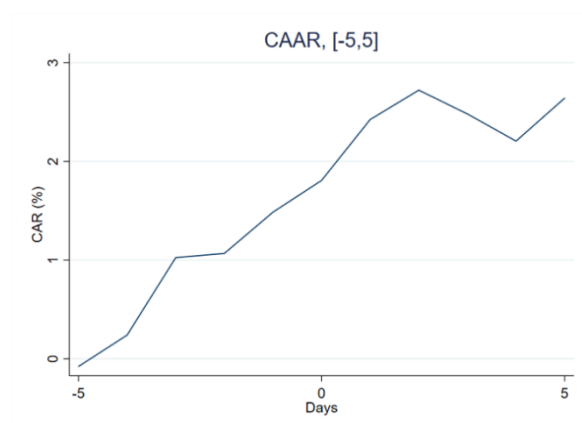
Source: Illustration by the authors and data from Thomson Reuters Eikon.

However, the result that group 2, including observations with a split factor of 0.5, shows a greater increase in return compared to group 1 deviates from earlier research within this field, as previous studies have shown split factor to have a positive relationship with abnormal returns (McNichols & Dravid, 1990).

Graph 1 shows the CAAR over time for all firms over the period -5 to +5 days around the announcement. This suggests that there is an increase in abnormal returns before the announcement, with the curve flattening and the returns stabilizing around 2 to 3 days after the announcement. These results indicate that the wider definition of event period of -5 to 5 days might be favorable compared to the -3 to 3 days interval, as it contains price movements which in all probability are linked to the announcement. Table 5 then displays a more detailed overlook of the daily average abnormal returns and confirms that there are significant positive abnormal returns before the announcement of the split.

Graph 1 – CAAR Displayed over time

Source: Illustration by the authors and data from Thomson Reuters Eikon.

Table 5 – Event study – AAR

Day	AAR
-5	0.2402%*
	(0.0972)
-4	1.1031%***
	(0.0001)
-3	0.8271%
	(0.1122)
-2	0.4604%
	(0.1868)
-1	0.7398%**
	(0.0214)
0	0.9389%**
	(0.0110)
1	0.9150%***
	(0.0019)
2	0.0567%
	(0.1733)
3	-0.5166%
	(0.2714)
4	0.1602%
	(0.8920)
5	0.1625%
	(0.5771)

*Notes: P-values in parenthesis. *p < 0.1; **p < .05; ***p < .01.*

Event study results per event date, counted from announcement day, using the Patell (1976) test, with the Kolari and Pynnonen (2011) adjustment.

Source: Illustration by the authors and data from Thomson Reuters Eikon

6.2.2 Modelling of abnormal returns

Table 6 displays the modelling of the dependent variable cumulative abnormal returns (CAR) through multivariate regressions, this by different combinations of the independent variables. The values for the cumulative abnormal returns (CAR) are the previous output from the event study, using the event window -5 to +5 days around the announcement day. Model 1 is using the variables liquidity, market value, and split factor with an interaction term between market value and liquidity. Model 1 yields no significant values for either liquidity, market value, split factor, or the interaction term. Model 2 introduces cumulative abnormal liquidity (CAL) to the model, which does not exhibit significance or affect the coefficients in any major way, however, it strengthens the significance for both liquidity and the interaction term, resulting in significance at the 10 % level.

Table 6 - Regression models using CAR – All Observations.

	Model 1	Model 2	Model 3
(Ln) Liquidity	*-26.263*	*-26.129**	*-36.284***
	(16.446)	*(14.505)*	*(15.307)*
(Ln) Market value	*-0.180*	*-0.252*	*1.421*
	(0.700)	*(0.585)*	*(0.890)*
Split-Factor	*1.115*	*1.053*	*-0.129*
	(1.992)	*(1.971)*	*(1.862)*
Cum. Abnormal Liq. (CAL)		*-0.139*	*-0.163*
		(0.180)	*(0.167)*
Analyst Coverage (AC)			*-0.369***
			(0.153)
(Ln) Market Value*(Ln) Liq.	*1.236*	*1.247**	*1.768***
	(0.746)	*(0.706)*	*(0.722)*
Constant	*5.468*	*7.658*	*-23.670*
	(15.572)	*(12.401)*	*(17.695)*
Adjusted R²	*0.0553*	*0.0802*	*0.1481*
N	**60**	**60**	**60**

Notes: Robust standard errors in parentheses. *p < 0.1; **p < .05; ***p < .01.

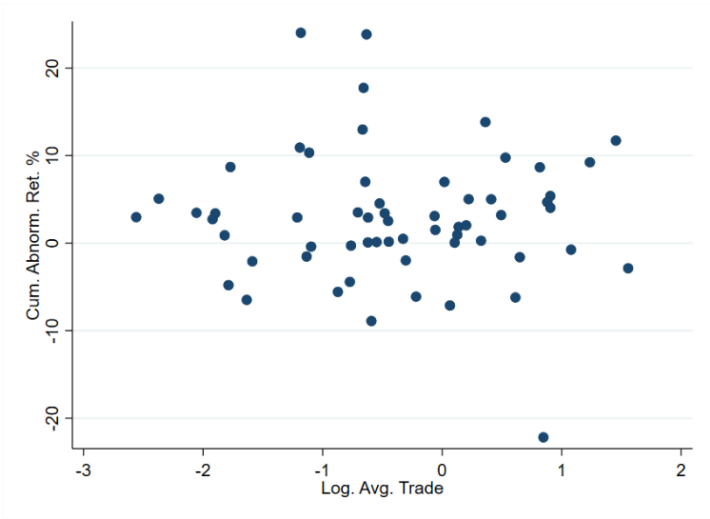*Source: Illustration by the authors and data from Thomson Reuters Eikon.*

The coefficient for liquidity implies a strong negative relationship with cumulative abnormal returns (CAR), suggesting a firm with lower liquidity could be assumed to have larger information asymmetry, the interaction term is however positive implying the negative relationship between liquidity and CAR is decreasing as the market value increases.

Introducing Analyst coverage in model 3 increases the size of both the liquidity and the interaction coefficient and increases their significance to the 5% level. Neither of the coefficients for market value, split factor or cumulative abnormal liquidity (CAL) do manage to surpass the threshold of the lowest conventional significance level. The coefficient for analyst coverage is however strongly significant above the 5 % level. Notably for further discussion about hypothesis 3, is the fact that both variables targeting information asymmetry, analyst coverage and liquidity, are significant when included together. The adjusted coefficient of determination (Adj. R^2) is further demonstrated. In model 3, where all variables are included, the adjusted coefficient of determination is 14.81%, which should be compared with previous studies. Grinblatt et al. (1984) report 27% while Ford et al. (2012) report 59%, hence this model has a lower level of adjusted coefficient of determination.

6.3 Extensions and robustness

Numerous tests were conducted to investigate the robustness of the results. Additional testing was specifically done in those cases where the variables were selected on a less solid theoretical basis, or when results deviated from what previous research has found. By observing table 2, containing descriptive statistics over the variables in the regression model by the number of observations, mean, standard deviation, minimum and maximum values, it is possible to distinguish potential problems with the data. Such a potential problem arises when observing the range of values for the CAR, which ranges from below -26.3 to 24.7, and that combined with an observed mean of 2.28 and a standard deviation of 8.35 suggests that the sample may contain potential outliers.

Graph 2 – Scatter over CAR and Liquidity

Source: Illustration by the authors and data from Thomson Reuters Eikon.

Table 9, in the appendix, allows a closer look at specific observations in the outer areas of the distribution, with the observation of U.S Physical Therapy heavily deviating with a CAR of -26.3%. This is also displayed in Graph 2, scattering CAR against liquidity and thus confirming the suspicion of a potential outlier, and an argument for potential exclusion.

Graph 3 - Scatter over CAR and CAL
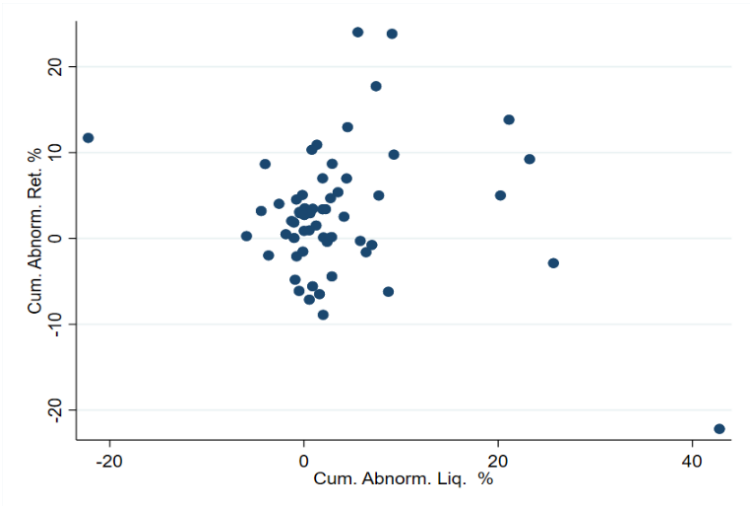
Source: Illustration by the authors and data from Thomson Reuters Eikon.

Further studies of table 2 also shows a wide range in the variable CAL with values ranging from - 22.2 to + 42.8 with a mean of 3.3 and a standard deviation of 8.7, thus demanding a further investigation of the variable. Using a scatter plot of CAL and CAR in graph 3, we observe both observations for the upper and lower bound can be confirmed outliers, J&J

Snack Foods being the lower bound observation, and the earlier discussed US Physical Therapy is the observation at the upper bound. Based on this, a new model was performed, copying table 6, but with the exclusion of these two observations, displayed in table 7.

Model 6 in table 7 exhibits lower but although still significant values for liquidity, analyst coverage, and the interaction term. This model, however, results in a significant positive value for CAL, contrary to model 3 with the inclusion of all observations. Given, the deviating values of US Physical Therapy, for both cumulative abnormal liquidity and cumulative abnormal return, this estimation of the coefficient is probably a better estimate of the real effect. This based on the idea that an increase in abnormal liquidity can be seen as an increase in the market interest for the firm. This version also results in a small increase in explanatory value, this in the form of an adjusted R^2 of 16.69 %, compared to 14.81 % in model 3.

Table 7 – Regression models using CAR – Excluding Outliers.

	Model 4	Model 5	Model 6
(Ln) Liquidity	-17.252	-15.891	-23.758*
	(11.578)	(12.471)	(13.594)
(Ln) Market value	-0.460	-0.293	0.954
	(0.513)	(0.560)	(0.804)
Split-Factor	0.104	0.490	-1.278
	(1.904)	(1.973)	(1.900)
Cum. Abnormal Liq. (CAL)		0.340*	0.265*
		(0.169)	(0.156)
Analyst Coverage (AC)			-0.279**
			(0.139)
(Ln) Market Value*(Ln) Liq.	0.830	0.726	1.132*
	(0.540)	(0.585)	(0.646)
Constant	12.586	8.034	-15.155
	(10.748)	(11.545)	(15.875)
Adjusted R²	0.0520	0.1219	0.1669
N	58	58	58

Notes: Robust standard errors in parentheses. *p < 0.1; **p < .05; ***p < .01.

Source: Illustration by the authors and data from Thomson Reuters Eikon.

The fact that there is a statistically significant correlation between constituent variables, seen in table 3, indicates multicollinearity, however, further investigation is needed as collinearity and correlation are not the same things. As a result, there may be multicollinearity even though there is no correlation between variables (Alin, 2010). One such test is the variance inflation factor, VIF. VIF measures the difference in the variance of an input variable when multicollinearity exists or does not exist (Alin, 2010). If VIF does not show any independent result higher than 10, it should not be considered problematic for the regression model (O'Brien, 2007). VIF is computed as below:

$$VIF_i = \frac{1}{1-R_i^2} \; for \; i = 1,2,....,k$$, where R_i^2 is the coefficient of determination for variable i (Alin, 2010).

The results in table 8 show that the mean value of VIF on the included variables does not differ significantly from 1.0, which indicates that this study has no problem with multicollinearity (Alin, 2010).

Table 8 – VIF-values

Variable	VIF
(Ln) Market Value	*3.28*
Analyst Coverage (AC)	*3.10*
(Ln) Liquidity	*1.37*
Cum. Abnormal Ret. (CAR)	*1.34*
Cum. Abnormal Liq. (CAL)	*1.10*
Mean VIF	**2.04**

Source: Illustration by the authors and data from Thomson Reuters Eikon

7. Analysis

7.1 Stock split announcements result in abnormal returns

Given the first hypothesis formulated, the results in table 4 support the occurrence of abnormal returns at the announcement of stock splits. Therefore supporting, like Grinblatt et al. (1984) propose, that a stock split is not just a cosmetic strategy made by the firm's management. There is thus an anomaly which, even though nothing fundamental for a firm's valuation has changed, still creates excess returns. Based on this, a semi efficient market is likely, at least on the Nasdaq Composite Index during the period 2001-2019. An interesting aspect that is visualized in the result is that abnormal returns are found prior to the announcement of a stock split. In practice, this implies two interesting conclusions. The first is that there is a leakage of private information from the firm to the market, which is captured by the average abnormal returns, table 5, even before the announcement, and that those who trade on the leaked insider information interpret a stock split as a positive signal. This positive pattern is also displayed once the firm has announced the stock split. As mentioned in section 3 of this thesis, there are various reasons why firms undergo a stock split. One of these theories is the signal hypothesis, that the firm's management holds positive private information, which is announced to the market through the stock split and results in abnormal returns (Fama et al.,1969; Grinblatt et al.,1984). Hence it should reasonably exist incentives for the management to implement a stock split. In addition to the fact that the announcement itself results in a higher share price from which the firm benefits, the firm's management owns shares in the firm through various incentive programs, which gives the management individual incentives to implement a stock split (Jensen & Murphy, 1990).

In line with our results, Ikenberry et al. (1996) demonstrate abnormal returns on stock splits and explain the anomaly by the management only carrying out a stock split if the management is optimistic about the future. Furthermore, Ikenberry et al. (1996) argue, in contrast to previously presented research that the abnormal return resulted from a stock split is permanent and not temporary, as Pilotte (1997) also confirms. Thus, there are reasons to suspect that the ownership structure also changes in connection with a stock split. If a stock split can only earn abnormal returns during the event window, it enables short-term investors (day-traders and swing-traders) to achieve an excess return during subsequent days when the

announcement takes place. Since Ikenberry et al. (1996) report long-run abnormal returns, it can be assumed that the interest from long-term investors should increase as well.

7.2 There is a negative relationship between liquidity and abnormal returns at stock split announcements

The result from this study regarding hypothesis 2, *There is a negative relationship between liquidity and abnormal returns at stock split announcements,* is somewhat ambiguous. This as liquidity, measured as the logarithm of average daily shares traded, shows no significance at conventional levels when included in model 1, it is first with the inclusion of CAL, in model 2 that the coefficient for liquidity reaches significant levels, at 10 %. The inclusion of analyst coverage then further increases its significance in model three 3 to the 5 % level.

Throughout all 3 models', liquidity is strongly negative, which supports the hypothesis of a negative relationship between liquidity and abnormal returns, however, the models also include an interaction term between liquidity and market value which complicates the interpretation. This interaction term is positive, which implies there is a positive relationship between liquidity and market value. This can be interpreted as that the negative relationship between liquidity and abnormal returns are stronger for firms with lower market value. In the extension, this means that the relationship between liquidity and abnormal returns would be positive for a firm with a large enough market value. Using the estimated coefficients from model 3, the marginal effect of liquidity upon CAR can be written as,

$$\frac{dCAR}{dLiquidity} = -36.284 + 1.768 \times (LN)Market\ Value \rightarrow$$

$$\frac{36.284}{1.768} = 20.523 \rightarrow$$

$$e^{20.523} = 818\ 513\ 133,1$$

Implying that the marginal effect of increased liquidity on abnormal returns is positive for firms with market values larger than approximately e [(20.523)] and negative for firms with a market value lower than e [(20.523)]. So according to these results, hypothesis 2 is supported for

firms with relatively low market value but not at higher market values. More precisely does model 3 suggests that the limit of market value for the change of sign in marginal effect of liquidity on abnormal returns goes by a market value of $e^{20.523}$ or $818 513 133.1.

A possible explanation for that the marginal effect of liquidity changes sign depending on the market value, might be the size of the information asymmetry. As previous research suggests, information asymmetry and market value have an inverse relationship, liquidity, therefore, works well as a proxy when firms are small and exhibit information asymmetry in accordance with theory (Ford et al., 2012).

However, the level of liquidity for larger firms, assuming the positive effect of liquidity is an extrapolation, does not matter as a proxy. Based on the results of Grinblatt et al. (1984), that the frequency of information is highly correlated with the firm size, it can be proposed that at a certain level of size, the firms are monotonized to an extent so that the information asymmetry is approximately the same.

7.3 Liquidity before stock split announcements can be used as a factor for proxying information asymmetry

As mentioned in 7.2, we find a significant negative relationship between liquidity and abnormal returns in connection with a stock split. However, a positive relationship between the interaction term, liquidity and market value, and the abnormal return are also found. In practice, this implies that the negative relationship between liquidity and the abnormal return is stronger for firms with lower market value. The implication is that firms with relatively low liquidity on lower levels of market value will earn a higher cumulative abnormal return on stock splits than firms with relatively high liquidity and the same low market value. However, at higher levels of market value, this same relationship is inverted.

Based on the fact that firms with relatively lower liquidity and lower levels of market value earn a higher cumulative abnormal return and Roulstone's (2003) results of a positive relationship between liquidity and analyst coverage, it can be assumed that these firms exhibit higher asymmetric information than large firms with higher liquidity. The implication is that when firms with lower liquidity and lower market value announce a stock split, it will create a greater market interest than the opposite, where the market interest is measured as a

cumulative abnormal return. If the information asymmetry is greater, it will generate a higher cumulative abnormal return during a stock split. From this, the study can assume that liquidity can be used as a proxy for information asymmetry and the hypothesis is supported. However, regression model 3 shows significant values for both liquidity and analyst coverage suggesting that both are informative for predicting abnormal returns in connection to stock splits. From the theoretical background of that analyst coverage in previous studies (Ford et al., 2012) has been proven to be a functioning proxy for information asymmetry, it is somewhat surprising that they are both significant when included together. It can either be the case that both variables explain different parts of information asymmetry, or that the variables have enough explanatory power of other factors driving abnormal returns, even when including another proxy for information asymmetry.

7.4 Split factors, the ratio of shares issued per existing shares, have a significant effect on abnormal returns

As the results show in table 6, this study finds no significance regarding the effect of the split factor on abnormal returns. Therefore, we are not able to support that the size of the split factor has any significant impact on abnormal returns in a stock split on the Nasdaq Composite Index between 2001-2019. This unlike previous research by McNicholas & Dravid (1990) and Ford et al. (2012).

There may be several reasons why the result does not reflect previous research. One of them is that this thesis may include too few groups and with too small differences in split factor between the groups. A better alternative might have been to increase the difference between the groups in terms of the split factor. In this thesis, the observations were grouped with respect to split factors of 1 and 0.5, of which a possibly better alternative would have been to use split factors of 0.5 and 2. This may have measured the effect of split factors on abnormal returns in a better way and thus visualizing a clearer pattern. Another important aspect to highlight is the approach to manage data. Since this study only collected firms from CRSP with split factors of 1 or 0.5, the observations were not completely randomized. An alternative way would have been to do as McNichols & Dravid (1990), who did not exclude and grouped the data based on certain split factors, but instead used split factors as a continuous variable. Furthermore, another explanation may be that there are too few observations included. In this thesis, a total of 60 observations were used, divided into 2 groups of 30 each. In comparison

with McNichols & Dravid (1990), who used 3015 observations, 60 observations can be considered too few, which is probably demonstrated in the various results. The risk of having too few observations is that an individual observation has too great an influence on the result, hence the results can be misleading. An example of this is outliers that do not demonstrate the actual effect but still occupy a large part of the test results. In summary, this study can therefore not support that the abnormal return can be attributed to the choice of split factors. This implies that the size of the split factor signals different levels of optimism presented by McNichols & Dravid (1990) cannot explain the abnormal return in this study. Hence, other factors are considered to be the cause for the result of abnormal returns in connection to a stock split.

8. Conclusion

The purpose of this study was to investigate if abnormal returns could be earned around stock splits. Furthermore, it also examines which factors may explain the abnormal returns. To achieve the purpose of this thesis, four hypotheses were formulated. A total of 2101 events on the Nasdaq Composite Index between the years 2001-2019 were collected from the Centre for Research in Security Prices (CRSP), where 60 randomly selected events made up the sample. Furthermore, data for historical stock prices, trading volumes, shares outstanding, analyst coverage, and market value have been obtained from Thomson Reuters Eikon. An event study has been designed for testing the hypothesis of abnormal returns associated with a stock split, and in testing the other hypotheses, a regression model has been constructed. The results from the event study and the regression model are discussed below.

Our first hypothesis is "Stock split announcements result in abnormal returns". The results show significant abnormal returns of 2.24% for a 7-day period as well as 2.64% for a 11-days period, which thus supports our first hypothesis. These results are in line with previous research on abnormal returns around stock splits and thus also confirms that a semi-efficient market is likely (Grinblatt et al., 1984). By using an event study, abnormal returns could be observed even before the announcement of a stock split. This implies that there is a leakage of information from the firm's management to the market and that the beneficiary investors classify the information as a positive signal.

The findings of this study indicate partially desirable results regarding the second hypothesis, "There is a negative relationship between liquidity and abnormal returns at stock split announcements". The regression shows significance for firms with low market value but not for higher levels, this implies that liquidity has a negative effect on the abnormal return for firms with low market values. Thus, proposing that at a certain level of size, the firms are monotonized to an extent that the information asymmetry is approximately the same. Based on this, the thesis only finds significant results for firms at lower market values regarding hypothesis two.

The results regarding the third hypothesis, "Liquidity before stock split announcements can be used as a factor for proxying information asymmetry", show that the variable liquidity exhibits negative correlation with abnormal returns up to a certain level of market value. This as the results show a negative effect of liquidity on abnormal returns as a standalone factor, but show a positive relationship when included in an interaction term with market value. These results, together with earlier confirmed research on the positive correlation between liquidity and analyst coverage implies that firms with low liquidity and market value will earn a higher abnormal return around stock splits. In turn, this may explain that firms with low media monitoring result in higher abnormal returns around stock splits. From this, our results indicate that hypothesis three can be supported, and thus that liquidity can be used as a proxy for information asymmetry.

Finally, the test reveals no significant results for the fourth hypothesis, "Split factors, the ratio of shares issued per existing shares, have a significant effect on abnormal returns". It is thus not possible to say whether the split factor can explain the abnormal return, which deviates from earlier research within this field (McNichols & Dravid, 1990). The most likely reason for this deviation is that this study only includes two groups of split factors, as opposed to earlier studies which includes a wider range. Therefore, we cannot find the earlier documented relationship between split factors and abnormal returns, and thus find no support for the fourth hypothesis.

For future research, it is proposed to use a larger sample, this to increase reliability and to avoid the influence of outliers which risks generating distorted results. Furthermore, it is of interest to test other measurements of liquidity. Previous studies have primarily concentrated on trading volume as a percentage of shares outstanding as well as the bid-ask spread as the measurement of liquidity. There is therefore of interest to use other measurement of liquidity to further analyse this type of market anomaly. Furthermore, as some of the factors discussed in theory about stock splits are non-numerical, there is a need for proxies to be used. Hence, it would be of interest to expand the use of different types of proxies, in order to measure the impact of non-numerical factors of the abnormal returns.

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Appendix

Table 9 – Detailed results from event study

Companies Split factor 2:1	CAAR [-3,3]	CAAR [-5,5]	Companies Split factor 3:2	CAAR [-3,3]	CAAR [-5,5]
J&J Snack	8,59%* (0.0732)	11,92%* (0.0503)	Sanderson Farms Inc	25,25%*** (0.00)	24,38%*** (0.000)
Microsoft	-2,44% (0.4874)	-3,93% (0.3773)	Fiserv Inc	-7,76% (0.2706)	-8,31% (0.3542)
T. ROWE	-4,81%* (0.0915)	-4,65% (0.1825)	Heartland Expr. Inc	0,61% (0.8703)	2,70% (0.5713)
American Woodmark	4,38% (0.2125)	10,13%** (0.0247)	Conmed Corp	0,58% (0.9386)	-2,92% (0.7601)
Dentsply	4,07% (0.1389)	1,55% (0.6571)	Dentsply	-1,52% (0.7286)	3,46% (0.5342)
Apple	8,35% (0.2195)	3,49% (0.6861)	Asso. Bancorp	2,74% (0.1861)	4,43%* (0.0910)
Applied Materials	5,98% (0.3876)	9,19% (0.2969)	Cantel Med. Corp	-4,09% (0.5976)	4,69% (0.6349)
Popular Inc	5,66%** (0.0296)	4,69% (0.1539)	MGE Energy	-0,60% (0.8098)	3,49% (0.2707)
Nordson Corp	-1,73% (0.4945)	14,26%*** (0.000)	Mercantile Bancorp	2,52% (0.6079)	2,63% (0.6742)
Ansys Inc	0,06% (0.9900)	9,98% (0.1277)	Middlesex Water	1,65% (0.7048)	2,98% (0.5925)
Adobe Inc	4,90% (0.1498)	5,39% (0.2131)	Progressive Corp	1,16% (0.7349)	2,52% (0.5624)
Ross Stores	2,12% (0.5924)	0,76% (0.8801)	ICU Medical	-5,33% (0.4460)	-7,75% (0.3826)
Matrix Service Co	5,70% (0.4593)	1,95% (0.8411)	Option Care	13,89%*** (0.0054)	14,21%** (0.0243)
Cathay Gen. Bancorp	5,26% (0.2236)	3,85% (0.4815)	US Phys. Therapy	-19,35% (0.2618)	-26,33% (0.2325)
CorVel Corp	-0,87% (0.7729)	-2,01% (0.6010)	Encore Wire Inc	0,38% (0.9667)	2,43% (0.8337)
Qualcomm Inc	-1,78% (0.6318)	-1,61% (0.7336)	Microchip Tech	10,25%* (0.0615)	10,95% (0.1156)
Synopsys Inc	-4,65% (0.3569)	-3,59% (0.5757)	Shoe Carnival	21,93%*** (0.0001)	18,92%*** (0.0064)
Fuelcell Energy Inc	-4,93% (0.7260)	-6,03% (0.7368)	First Financial Bank	6,15%* (0.0732)	4,75% (0.2700)
Patterson Comp. Inc	-2,15% (0.5650)	-1,61% (0.7347)	Forward Air Corp	-2,71% (0.5002)	0,90% (0.8610)
Intuit Inc	1,16% (0.7983)	1,64% (0.7807)	Copart Inc	2,32% (0.7652)	2,43% (0.8059)
O'Reilly Automotive	-3,12% (0.3197)	-2,27% (0.5725)	Dollar Tree Inc	-1,38% (0.7585)	3,82% (0.5043)
Blizzard Act.	9,43%* (0.0712)	14,38%** (0.0311)	Sandy Spring	-0,30% (0.9634)	-4,86% (0.5576)
Hain Celestial Inc.	4,93% (0.2156)	1,25% (0.8040)	Wintrust Fin. Corp	6,04% (0.2567)	3,42% (0.6125)
Matthews Int. Corp.	4,26% (0.3373)	0,97% (0.8639)	Columbia Sports	19,40%** (0.0350)	24,67%** (0.0363)
Nvidia Corp	2,44% (0.6069)	3,19% (0.5970)	Nvidia Corp	5,41% (0.2943)	-2,97% (0.6535)
Dollar Tree Inc	5,58%* (0.0638)	-0,33% (0.9320)	Glacier Media Inc	4,26% (0.1110)	3,88% (0.2527)
Lincoln Electric Inc.	-1,74% (0.4151)	-2,23% (0.4104)	Indep. Bank Michiga.	-6,49% (0.2049)	-8,35% (0.2000)
Myriad Gen. Inc	-7,47% (0.3322)	-9,49% (0.3343)	LSI Indu.	5,09% (0.5243)	12,38% (0.2247)
Resources Connecti.	0,41% (0.9486)	-7,09% (0.3807)	Comcast Corp	-3,61% (0.1947)	-10,20%*** (0.0045)
Woodward Inc	-1,19% (0.8173)	0,15% (0.9823)	Meridian Bio.	-2,70% (0.7093)	0,97% (0.9160)
CAAR	1,66%* (0.0591)	2,00%** (0.0430)	CAAR	2,81%*** (0.0030)	3,26%*** (0.0080)

Notes: P-values in parentheses. *p < 0.1; **p < .05; ***p < .01.

Source: Illustration by the authors and data from Thomson Reuters Eikon.