Abnormal Returns in Merger and Acquisition Announcements in the Telecommunication Industry

An event study approach

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"Successful enterprises are built from the ground up. You can't assemble them with a bunch of acquisitions"

- *Louis V. Gerstner Jr.*

Abstract

Since the turn of the millennia, the volume of M&A deals in the telecommunication industry has increased enormously, much due to deregulation and increased globalization. Prior to the 1990s, the industry was nearly fully monopolized, consisting of giant national and regional operators (Warf, 2003). Since then, rapid innovation and deregulation has intensified the industry's competitiveness. Corporate consolidation has become a prevalent strategy in ensuring competitiveness and survival. Resulting in the question of whether pursuing this strategy is the optimal decision in terms of value creation. Several econometric studies have analyzed the stock reaction following announcements of mergers and acquisitions. However, a majority of such studies target either the general M&A announcement reaction across all industries or focus outside the telecommunication industry.

This paper distinguishes itself from existing theory, by investigating the effect of both firm-specific and deal-specific variables on abnormal returns of the acquiring firm following a merger announcement. In addition, this paper aims at exploring whether the reaction on abnormal returns and its explanatory variables varies across geographical regions. The period of investigation spans from January 1st, 1998 to 31st of December, 2016, and the market model is applied to calculate the deviation between expected and realized returns surrounding the days of the M&A announcement. By analyzing the isolated effect on abnormal returns, we find interesting deviations across regions, questioning the hypothesis of efficient markets and investors' putative rational behavior. Furthermore, through estimating the effect of 18 independent variables on abnormal returns, this paper reveals new findings of numerous variables having a significant effect on abnormal returns.

Key words: *M&A, mergers, acquisitions, abnormal returns, telecommunication, market model, regression*

Preface

This thesis is written as a part of the compulsory requirements for completing our MSc in Applied Economics and Finance at Copenhagen Business School. The paper constitutes 30 ECTS and has been written in the period from January 25th to May 11th. We assume all information provided in this paper is correctly portrayed. Nevertheless, due to the limited time span, we have not verified the variables applied other than cross-checking multiple databases. Hence, we disclaim any financial or legal liability to the accuracy or comprehensiveness of the results presented.

Furthermore, there are several people we would like to thank. First, we would like to thank our supervisor, Martin Linnemann Larsen. Martin's practical experience regarding mergers and acquisitions have provided us with valuable insight into different areas that are important to recognize when writing the thesis. In addition, we would like to thank Einar Bjering for contributing with his expertise on mergers in the telecommunication industry. We would also thank Lisbeth La Cour and Niklas Maltzahn for helping us with econometric intuition regarding both the variable and model selection. Finally, we would like to thank our family and friends, who have provided us with their support, not only through the process of writing this thesis but throughout our two years at CBS.

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1.0 Introduction

The questions of whether announcements of merger and acquisitions are informative to investors, and how investors react to such announcements, have been a subject of research in multiple papers and articles over the past few decades. After the enormous wave of M&A following the revision of the Telecommunication Act and the WTO agreement in 1996 and 1997, global telecommunication (hereafter, telecom) companies have gone through major reconfigurations in their corporate structure (Park, Yang, Nam, & Ha, 2002). The need for constant change due to a dynamic business environment motivates companies within the sector to look for expansion through merging with other companies (Shah & Arora, 2014). Reduced entry barriers to foreign countries are among the factors triggering a worldwide competition; activating the movement of global M&A.

It is commonly believed that merger activity strengthens businesses within telecom through making operations more synergetic and providing advantages tied to, e.g., cost reduction, diversification and market power (Park et al., 2001). However, several empirical studies have challenged this assertion and found that mergers could either be value-destroying or have no significant effect on the value created for the shareholders of telecom companies (Bruner, 2004). Companies within the telecom industry are facing challenges of convergence, business transformation, technological change, regulatory pressure and growth. This presents a question of whether pledging merger deals is the optimal business strategy to pursue, or if the risk of destroying value rather than creating profit is too decisive.

Given the limited number of studies explicitly addressing which factors affect the M&A transactions in the telecom industry, we aim to bridge this gap by examining the variation of firm-specific and deal-specific factors on abnormal returns of large telecom firms on a global scale. As previous empirical work on M&A transactions are nearly unanimous regarding the returns to targets (the firms being bought) being significantly positive (Jensen & Ruback, 1983) (Trifts & Scanlon, 1987), we have decided to focus our study on the returns of the acquiring firm. Thus, we are studying the effect of M&A deals on the acquirers' share price. In order to execute this analysis, we will apply an event study methodology to be able to investigate the "*abnormal return of companies before, during, and after a common type of event, where the goal is to analyze whether the event has any influence on the company's share price*" (Patricksson & Evans, 2016).

Our thesis aims to build on existing literature, and to provide some further insights into the stock price reaction following a merger announcement. Besides explaining the quantitative, econometric results, we also

wish to contribute to this with a discussion on how human perceptions and behavioral finance might be a reason for potential violations of the hypothesis of efficient markets.

Consequently, we want to answer the following research question:

Does the semi-strong form of the efficient market hypothesis hold in the case of merger and acquisition announcements in the telecommunication industry?

To further justify potential breaches of the Efficient Market Hypothesis (EMH), we will further investigate movements in explanatory variables on abnormal returns by asking the following question:

Are there any firm-specific or deal-specific factors affecting the effect of M&A announcements on abnormal returns and do these vary across geographical regions?

The firm-specific factors are defined as characteristics of the acquirer, while the deal-specific variables refer to elements of each individual deal. Additionally, we control for several external variables that we believe could have an impact on the shareholder value.

To answer these questions, we will employ various statistical models. First, we will use a conventional t-test to find the isolated effect on abnormal returns resulting from a merger announcement. Second, we will evaluate the impact of different explanatory factors on abnormal returns by using a multiple regression model. Our underlying belief is that there are both firm-specific and deal-specific factors affecting the stock return reaction. As earlier empirical literature is inconclusive in their findings on the significance of abnormal returns around the event date, we will expect to potentially observe regional differences.

Furthermore, we will break down our analysis in five different hypotheses where we take a closer look into the dynamics of the abnormal returns as well as their potentially explanatory variables across different regions. Additionally, we have chosen to run and investigate the effect on the global sample, as well as isolating certain geographical areas to look for similarities and differences. Altogether, we are interested in

examining the presence of a consensus of the effects caused by merger announcements on abnormal returns across regions.

This paper is divided into nine different sections, starting off with the *Introduction* in *Section 1*, followed by Section 2, covering the *Literature Review* where we present some background information and earlier empirical literature on market efficiency surrounding the event of M&A announcements. Furthermore, Section 3 and Section 4 present and review the *Methodology* and the *Sample and Data* employed in the analysis. Next, Section 5 introduces and explains the five *Hypotheses* of the paper that establish the structure in the remaining section of the thesis. Section 6 and Section 7 present and elaborate the *Results* of the analysis and provide a *Discussion* of our findings compared to earlier empirical findings. In Section 8, we will reflect on the *Limitations* of the thesis, identifying its possible restrictions in scope and usage, before we provide a final *Conclusion* in Section 9.

2.0 Literature review

2.1 How are M&A defined?

The term *mergers and acquisitions* (M&A) is defined as "*the combination of two or more companies into one new company or corporation"* (Roberts, Wallace, & Moles, 2003). Although commonly used as synonyms, the two terms differ, mainly tied to how the combination of the two firms is structured. There are several definitions of both mergers and acquisitions. Hampton (1989) defines a merger as "*a combination of two or more businesses in which only one of the corporations survive".* Based on the classification in other papers we find Singh's (1971) definition more fitting as he states that in a merger, two or more firms are united and together form a "new" firm. Singh further defines an acquisition as a takeover where one firm buys a controlling stake, more than 50%, of the target. The legal structure and the name of the acquiring firm do not change, while the target either keeps its name and structure or ceases to exist (Roberts, Wallace, & Moles, 2003). Although there are some differences in the definition of mergers and acquisitions, they are inconsequential to out use in this thesis, Therefore, we will refer to both when using the general term *mergers and acquisitions*, M&A or just *mergers*.

M&A can be further categorized based on the relation between the firms involved. There are mainly three different types of mergers: horizontal, vertical and conglomerate. A horizontal merger refers to a transaction where the acquirer and the target operate in the same industry, whereas if two companies in the same supply chain, but not necessarily the same industry merge, it is called a vertical merger. Finally, a conglomerate merger is defined as a merger between two companies in unrelated industries (Berk & DeMarzo, 2013).

2.2 M&A in the Telecom industry

Since the 1990s there have been numerous M&A transactions in the telecommunication industry, particularly in the US and Europe. This increase in M&A activity can mainly be tied to three different incidents. Starting with the alteration of the US Telecommunication Act in 1996, followed by the agreement covering basic telecommunication in the World Trade Organization (WTO) in 1997, and lastly the unification of the European Union in 1998.

When discussing M&A in the US telecommunication industry, it is natural to start with what has been referred to as the most important regulatory change since the 1930s, the Telecommunication Act of 1996 (Atkin, Lau, & Lin, 2006) (Howard, 1998) (Schaefer & Birkland, 2006). The industry had changed dramatically since the 1930s, and the resolutions from the former Telecommunication Act of 1934 became more and more

insufficient in handling modern challenges. The idea behind the legislation was to remove cross-entry barriers that had been put in place by a similar act in 1984 (Krattenmaker, 1996). By removing said barriers, the men behind the act imagined that the industry would emerge from a monopolistic market to a more open and competing market (Bates, Albright, & Washington, 2002). In its own words, the act aimed "*To promote competition and reduce regulation in order to secure lower prices and higher quality services for American telecommunications consumers and encourage the rapid deployment of new telecommunications technologies"* (US Government, 1996).

However, the act failed to create the competitive market it was designed to establish. Directly after the legislation passed, there were a lot of big mergers and acquisitions, leaving the industry with a small number of dominating conglomerates. The high number of mergers in the telecommunication industry continued into the new millennium, and it is safe to say that the Telecommunication Act of 1996 was unsuccessful in creating the competitive market it was meant to construct. In fact, the Act of 1996 contributed in making the telecommunication industry one of the most concentrated industries in the world. In 2013 the concentration ratio of the top four firms (CR4) ranged from 85.8% to 95.1% depending on sub-industry; making it a highly concentrated industry (Fu, Mou, & Atkin, 2015) (Kahn, 2013) (Kahn, 2014). A high concentration can suppress competition and affect customers negatively by limiting the options and information sources and increasing firms' market power. Top firms can use their market power to boost rates, while simultaneously decreasing the quality of a given product (W. McChesney, 2000) (Albarran & Dimmick, 1996) (Chan-Olmsted & Litman, 1988).

In Europe, deregulation and free competition promoted by the European Union (EU) changed the telecommunication market into a liberalization process. Historically, the European markets had been monopolized, but after the implementation of general competition rules within the EU, an M&A-wave of cross-border M&A characterized the market (Park et al., 2002). The Asian market did not follow the same pattern as Europe and the US. In the late 1990s and the beginning of 2000s the use of domestic merger transactions dominated the Asian market, while at the same time, the European market was dominated by cross-border mergers. Several big Japanese firms used M&A to increase their market power at a regional level (Park et al., 2002).

On a global level, the aforementioned agreement by WTO regarding basic telecommunication in 1997 was essential. The participants agreed to set aside domestic differences and find a common set of trade rules covering basic telecommunication. The agreement secured a liberalization of the global telecommunication

industry, and the coverage of several of the agreements WTO manages, notably the General Agreement of Trade in Services (GATS). Especially noteworthy is the three articles covering (1) Domestic regulations, (2) Monopolies and exclusive service providers, and (3) Business practices, are relevant based on the monopolistic tendencies in the industry and the possibilities this creates for predatory behavior (World Trade Organization, 1997).

Figure 2.1: The evolvement of the MSCI World Index versus three Telecom-specific indices
Source: Datastream (2018)

As can be seen from Figure 2.1 above, the telecommunication industry outperformed the market until the burst of the dot-com bubble in March 2000 and has underperformed ever since. The graph also indicates that the telecommunication industry follows the same trends as the general market, illustrated by the similarities in market movements.

2.3 Dynamics of the Telecommunication Industry

To make the merger culture within Telecommunications easier to grasp, an elaboration of the dynamics and structure of the industry is necessary. For us to better understand the complexity of the Telecom value chain, we did an interview with consultant Einar Bjering. According to Bjering (Personal communication, February 26, 2018), the value chain of the Telecom Industry can be separated into three different areas. First, we have the *Hardware Producers*, who manufacture the various components needed when operating a network. Second, the *Mobile Network Operators* (MNO) builds, maintains and owns the networks. Lastly, there are the *Mobile Virtual Network Operators* (MVNO) being network service resellers who do not possess their own

infrastructure. Thus, the MVNOs rent the network of the MNOs at a premium to acquire the required capacity from other telecom carriers (E. Bjering, personal communication, February 26, 2018).

MNOs such as Verizon Wireless and Orange chose to lease the network capacity to MVNOs as they have extra capacity that would otherwise be unused. Hence, rather than taking a loss, they earn a small profit by offloading parts of the network capacity at wholesale prices. On the other side, MVNOs can afford to lower their retail prices, since they have no costly infrastructure to build or maintain. Besides, due to the low overhead costs, they can allocate their resources toward marketing to increase the number of customers (Federal Communication Commission, 2008). To illustrate the dynamics value chain, we will provide an overview of well-known companies divided into the different areas of operations as presented in Figure 2.2. The categorization of the various companies in Figure 2.2 is based on information retrieved from the respective companies' websites.

Figure 2.2: The Telecom Value Chain with Examples of Companies

However, there is a problem of definition in cases where acquiring companies operate in more than one part of the value chain. In Figure 2.2, it can be observed that *AT&T Technologies* are among the companies operating across parts of the value chain, as they are an MNO who also provides hardware manufacturing. Hence, the aim of positioning all individual companies within the given frames of operations will be challenging and potentially create inaccurate and false interpretations. This is especially true of the utilization in quantitative context, as some fair assessment may need to be applied when defining implications of value chains across borders.

2.4 Why do companies merge?

Most literature on the wealth effect of acquiring firms has found a negative effect on the said firms' stock price (Park et al., 2002) (Moeller, Schlingemann, & Stulz, 2005) (Baker & Kiymaz, 2008). If this is true for all industries, why do companies continue to undertake expensive mergers and acquisitions in an attempt to generate wealth? Several theories have been developed with the purpose of explaining why mergers occur. The motives for merging presented in this paper will mainly be the ones suggested by Seth (1990) and Berk and DeMarzo (2013), though, supplemented with insights from other authors.

Seth (1990) categorizes mergers within two main groups: *value-maximizing* and *non-value-maximizing*. He defines value-maximizing mergers as mergers that "*are motivated by maximizing the value of the firm to stockholders"* (Seth, 1990). Non-value-maximizing mergers, on the other hand, are defined as mergers where the managers use the mergers to "*maximize their own utility at the expense of stockholders"* (Seth, 1990). The value-maximizing theory states that a merger generates a value creation that increases the wealth of shareholders for both parties. On the contrary, the non-value-maximizing theory claims that the merger may not be value creating and that any wealth created is absorbed by the shareholders of the target firm, while the wealth of the shareholders of the acquiring firm decreases (Seth, 1990).

Synergy effects are the most common reason behind mergers and are usually split into two different groups: cost reductions and revenue enhancements. By comparison, cost reduction is often more straightforward to accomplish, as a merger usually generates duplicates, both regarding employees and other assets. Hence, getting rid of these duplicates in the newly formed company reduces the overall costs, relative to the case where the company operated in separate units (Berk & DeMarzo, 2013). If chasing synergies is the reason behind a merger, the motive is value-maximizing. Multiple different motives may be behind a value-maximizing merger. Examples of these are (1) market power, (2) economies of scope, (3) economies of scale and (4) financial diversification (Seth, 1990).

The first motive is *market power* which Stigler (1968) defines as "*the ability of a market participant or group of participants to control the price, the quantity or the nature of the products sold, thereby generating extra-normal profits"* (Stigler, 1968). Market power is a common motive for mergers within the telecommunication industry emphasized by Einar Bjering (Personal communication, February 26, 2018). He states that one of the most common types of mergers seen over the last five years is horizontal mergers where big telecommunication companies like Telia, buy smaller similar companies to obtain their customers (E. Bjering, personal communication, February 26, 2018).

The second motive behind mergers is *economies of scope*. Economies of scope occur when the total costs of joint production by one merged company is lower than the cost of production by two separate companies (Seth, 1990). The gains from economies of scope are expected to be higher in mergers between similar companies, given the related nature of their product line. Berk and DeMarzo (2013) emphasize this in their definition by stating that economies of scope are "*savings large companies can realize that come from combining the marketing and distribution of different types of related products"* (Berk & DeMarzo, 2013).

The third motive behind M&A is *economies of scale*. Berk and DeMarzo (2013) describe economies of scale as savings a large company can experience when producing a high volume of goods. Economies of scale are commonly seen as a motive between companies utilizing shared materials or goods (Seth, 1990). It could also be achieved by combining other parts of the business, like distribution, research and development, service networks, and advertising (Porter, 1980) (Scherer, 1980). The telecommunication industry generally experiences high fixed costs and relatively low marginal costs, which generates a vast potential for both economies of scope and scale (Rieck, 2010), (E. Bjering, personal communication, February 26, 2018). A reason why some mergers with scope and scale motives do not create any positive wealth effects for the involved parties is that the potential synergy effects are hard to achieve. Even though companies are similar in operations and the use of resources, diversity in corporate culture and significant integration costs offer further reasons for why the desired wealth effect does not show (Rieck, 2010).

A fourth merger motive presented by Seth (1990) and Berk and DeMarzo (2013) is *financial diversification*. A diversification merger aims to reduce the financial risk of a company by acquiring a firm with another business cycle than its own to reduce the variance of the firm's returns (Seth, 1990). Based on the requirements of different business cycles, mergers motivated by financial diversification are exclusively conglomerate mergers (Berk & DeMarzo, 2013) (Hughes, C. Mueller, & Singh, 1980). Financial risk can be

divided into two separate parts; systematic and unsystematic risk. By assuming perfect capital markets, only the unsystematic risk can be affected by a diversification motivated merger. Given that systematic risk is the solely significant underlying factor of a security's price, a merger aimed at diversification is not expected to create any value for the acquiring firm (Seth, 1990) (Berk & DeMarzo, 2013).

While all the motives mentioned so far are categorized as value-maximizing, there are additional motives behind mergers that can be classified as non-value-maximizing. The managers themselves often promote these motives, and previous literature has shown a reduction in the stock price of the acquirer after an announcement of these kinds of mergers (Berk & DeMarzo, 2013). The first possible explanation of this reduction is a conflict of interest between the manager and the board of directors. Given that a manager's salary is often closely tied to financial performance, but less tied to potential losses, they would prefer to be in charge of a larger company given the expected rise in salary (Berk & DeMarzo, 2013). Another reason might be due to overconfidence. Richard Roll (1986) argued that overconfident managers often thought so highly of their abilities to lead that they alone could turn a merger of low possibilities of success into a positive wealth effect. The difference between these two explanations of non-value-maximizing mergers is that under the first scenario, managers are aware of the destruction of value. In the second case they believe that they are doing the right thing but misjudge their own capabilities (Berk & DeMarzo, 2013).

2.5 Merger Waves

The volume of merger transactions has historically proven to follow specific patterns, commonly referred to as merger waves. Based on historical data, merger activity increases in periods of economic growth and declines during recessions (Berk & DeMarzo, 2013). Previous research on M&A suggests that mergers usually happen in waves that are clustered by industry (Mitchell & Mulherin, 1996) (Andrade, Mitchell, & Stafford, 2001) (Harford, 2005). Mitchell and Mulherin (1996) used a neoclassical framework when discussing the dynamics of industry structure. They assume that the structure of an industry, given by the number and size of firms, is a function of factors such as supply and demand conditions, technology, and government policies. Any changes in these factors would change the industry structure, generate a need for asset reallocation, and as a response, the number of mergers could increase.

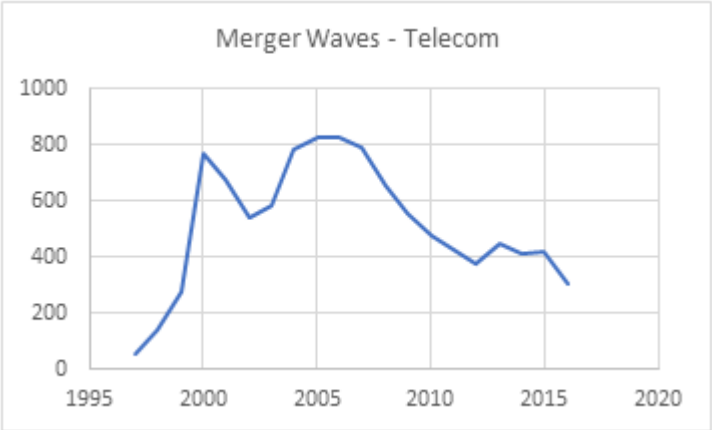

Figure 2.3: Merger Waves in the Telecommunication Industry from 1996-2016
Source: Zephyr (2018)

This is supported by Harford (2005), who concludes that the main driving force behind merger waves is industry shocks; such as technology, regulatory and economic shocks. One important addition to previous literature is the emphasis on sufficient overall liquidity. Harford's findings suggest that the "*liquidity component causes industry merger waves to cluster in time even if industry shocks do not*" (Harford, 2005). This indicates that to afford the needed asset reallocation, there has to be adequate capital liquidity, and the shocks are therefore not sufficient by themselves to create a wave. Thus, merger waves can be explained relatively straightforward: they demand an economic shock to motivate transactions and somewhat low transaction costs to generate a high number of transactions.

2.5 The Efficient Market Hypothesis

The American economist Eugene Fama developed the Efficient Market Hypothesis - the notion that markets accurately, thoroughly and instantaneously incorporate all available information in the market prices. A precondition of the strong form of this theory is that the cost of information and trading costs are always equal to zero (Fama, 1991). In theory, this makes it impossible to earn excess returns by outperforming the market without engaging in riskier investments. With thousands of advisory services, a tremendous amount of information, as well as millions of investors, the adjustment of prices to new information is approximately instantaneous (University of Windsor, u.d.).

The model assumes that (1) successive price changes must be *independent* and that (2) successive returns must *conform to some probability distribution*, for the EMH to be consistent (Fama E. , 1965). Fama (1965), states that "*a situation where successive price changes are independent is consistent with the existence of an "efficient" market for securities, that is, a market where, given the available information, actual prices at*

every point in time represent very good estimates of intrinsic values". Nevertheless, in a world of uncertainty, the intrinsic values do not necessarily correspond to the actual market prices. The uncertainty relates to the intrinsic values being dependent on the earnings prospects of the company, which in turn are dependent on political and economic factors. Some of these factors are firm-specific while others affect the respective industry and/or the overall market. Hence, uncertainty regarding intrinsic values is characterized as “noise” in the market (Fama, 1965).

The question of to what extent historical information can provide meaningful predictability concerning future stock prices has been a source of continuing controversy in both academic and business circles for several years. Provided solutions can be separated into two different views: (1) chartist (technical analysts) theories and (2) the theory of random walks. The chartist theories all make the same assumption, assuming that past behavior of a security provides a high degree of information concerning future price behavior by identifying specific patterns. Conversely, the random walk theory states: "*the future path of the price level of a security is no more predictable than the path of a series of cumulated random numbers”* (Fama E. , 1965). Hence, unlike the chartist view, the random walk theory is unable to predict future stock prices in a meaningful way (Fama, 1965). The random walk model has, however, been proven to be highly useful when conducting tests regarding the efficient market hypothesis, especially the weak-form stock market efficiency.

According to Fama, there are three sufficient conditions for capital market efficiency:

1. The transaction costs of trading securities are equal to zero.
2. All available information is equally available for all market participants without any costs.
3. All market participants agree on the implications of the available information on the current price as well as the distribution of the future security development

Source: (Fama, 1970)

When all three conditions are fulfilled, the securities are by definition "fully reflecting" all available information. However, such a frictionless market neglects the fact that in reality, information is not necessarily freely available, and investors do not always agree on its implications. Fortunately, the market could still be efficient without meeting all three conditions. For example, if an "adequate number" of investors have access to all available information the market may be efficient (Fama, 1970).

Grossman and Stiglitz (1980) argue that prices are not able to reflect all available information. This results from the fact that information is costly and agents who invest resources in obtaining the information would receive no sufficient compensation. They state, "*there is a fundamental conflict between efficiency with which markets spread information and incentives to acquire information*" (Grossman & Stiglitz, 1980). Furthermore, they conclude that the more expensive the information, the lower number of individuals would be informed. When a limited number of individuals are notified, this will lower the degree of available information reflected by the market prices.

Even though the EMH is an important concept with increasing acceptation after Fama's first papers on market efficiency (Fama, 1970) (Fama, 1965), it is also the subject of dispute and criticism. Researchers argue that the assumption that all investors are fully rational and always processing all available information correctly is unrealistic. One of the groups who have been critical of this are those adhering to the behavioral perspective of psychologists and experimental economists documenting departures from rationality and behavioral biases that tend to appear in human decision making under uncertainty (Lo, 2010).

Some studies argue that under- and overreaction cause market inefficiency when stock prices respond to information. However, consistent with an efficient market, apparent underreaction will be approximately as frequent as an overreaction. A roughly even split between under- and overreaction reflects anomalies in the market that do not necessarily have to cause market inefficiency. Additionally, Fama (1997) finds that "*post-event continuation of pre-event abnormal returns is about as frequent as post-event reversal*". Both pieces of evidence imply that that market efficiency does not have to be discarded; supporting market efficiency's feasibility (Fama, 1997). In his paper published in 1970, Fama divided the EMH into three relevant information subsets; weak form, semi-strong and strong tests (Fama, 1970).

2.5.1 Weak form

"*A market is said to be weak-form efficient if current security prices completely incorporate the information contained in past prices*" (Fama, 1970). The weak-form EMH is not able to forecast future prices and is thereby incapable of earning extraordinary profits (University of Windsor, u.d.). Introducing the question of whether past returns can predict future returns. As solely historical data reflect the current market price, the available information will not be able to forecast new movements in the price of securities by looking at old shifts in the market.

According to Fama (1965), random walk tests have been applied to test the weak form of the EMH. These tests state that the future development of a security's price is no more predictable than the path of series of accumulated random numbers (Fama, 1965). The random walk theory states, "*Successive price changes are independent, identically distributed random variables*". The tests serve their purpose as they strongly support the EMH (Fama, 1970).

Two decades later, Fama (1991) published an updated paper "Efficient Capital Markets: II", where he renamed the three different information subsets of market efficiency. The weak form category changed to "*test for return predictability*", which in addition to having forecasting power on past returns, includes forecasting of variables like dividend yields and interest rates. The extension is a result of his beliefs that various term-structure variables utilize prediction of future returns (Fama, 1991).

2.5.2 Semi-strong form

"*A market is said to be semi strong-form efficient if current prices incorporate all publicly available information*" (Fama E. , 1970). As opposed to the weak form, the available information now includes earnings/dividend announcements, multiple-ratios, news about the economy, political news, etc. (University of Windsor, u.d.). Generally, the semi-strong form of EMH investigates whether current market prices "fully reflect" all public information. However, each test focuses on price adjustments tied to one kind of information generating event (e.g., earnings announcements, mergers and acquisitions, stock splits, etc.). Only when evidence supports an accumulation of all individual tests, is the model considered valid (Fama, 1970).

Surveys on market efficiency, such as Fama (1970) (1991), focused on testing informational efficiency. They concluded that various empirical evidence is supportive of the weak and semi-strong form of efficiency. However, the most updated study of Fama (1991) reports even stronger evidence of predictability of returns both based on historical data and publicly available information, namely the semi-strong form (Fama, 1991). In addition, Fama (1970) confirms that available semi-strong form evidence of different types of a public announcement on common stock returns is overall significantly consistent with the theory of efficient markets (Timmermann & Granger, 2004).

When Fama published his article in 1991, he changed the name of semi-strong form tests of efficiency to "event studies" (Fama, 1991). At that point, the event study methodology had increased rapidly for over 20 years; made possible by powerful computers and CRSP (Center for Research in Security Prices) data. Fama

claims that the most direct evidence of market efficiency is the fact that it allows a break between market efficiency and equilibrium pricing issues (Fama, 1991). The event study methodology provides ways of documenting regularities in the response of stock prices to investment and financial decisions and hereby passes the test of scientific usefulness (Fama, 1991).

2.5.3 Strong form

"*At the extreme, a market is strong-form efficient if current prices reflect all information - public and private, including inside information; inside information is information about a firm which is available only to "insiders" including corporate executives and major shareholders*" (Fama, 1970). Evidence seems to indicate that such valuable insider information does not exist without incurring any additional costs. Hence, the hypothesis is undoubtedly false (University of Windsor, u.d.).

The strong form of the EMH is, for above-mentioned reasons, not expected to hold in reality. As insider information is not enough to give investors an advantage, the existence of abnormal returns is not present. However, the strong form efficiency is considered a benchmark in which investors can judge the importance of deviations from market efficiency. Barnes (2009) argued that due to the fact that the possibility of gaining profit from inside information exists, a strong-form efficiency could not exist (Barnes, 2009).

Instead of the strong-form efficiency test, Fama (1991) proposed the new title "tests for private information" (Fama, 1991). The new evidence brought to life by Fama's new paper only clarifies proof that corporate insiders have access to private information that not fully reflects market prices (Fama, 1991).

2.6 Market Anomalies

The theory of efficient markets reached its high in the academic circles in the 1970s. However, the succession of discoveries of market anomalies, mainly in the 1980s, brought a more nuanced view of the value of the EMH. In 1970, Fama pointed out that anomalies existed, though by emphasizing how small the anomalies were. Even though the anomalies did not seem to square with the EMH, the evidence against the hypothesis was not considered significant. However, Michael C. Jensen (1978) stated "*we seem to be entering a stage where widely scattered and as yet incohesive evidence is arising which seems to be inconsistent with the theory*". Through further increased availability of data (e.g., daily stock data) and the development of more sophisticated econometric programs, inconsistencies in EMH have appeared. It will be necessary to review

these scattered fragments of anomalous evidence regarding market efficiency as a whole to be able to accept the EMH and the methodological producers applied (Jensen M., 1978).

2.6.1 The January Effect

The January effect is defined as a seasonal increase in the price of securities in the month of January. Analysts generally explain the phenomenon resulting in the price drop that typically happens in December when investor engages in tax-loss harvesting to offset realized capital gains. In turn, this tends to increase by buying the following month (Thaler, 1987). Rozeff and Kinney (1976) found seasonal patterns in an equally weighted portfolio in the NYSE (New York Stock Exchange) index over the period 1904-74. Specifically, they found that the average monthly return in January was 3.5 %, compared to the other months which averaged at about 0.5 %. Using an equal-weighted index suggest that this is primarily a small firm occurrence (Rozeff & Kinney Jr., 1976).

2.6.2 The Monday Effect

The theory of *the Monday effect* states that stock market returns on Mondays will follow the trend from the previous Friday (Wang, Erickson, & Li, 2012). Empirical evidence from 1962-1993 proves that the effect occurs primarily in the last two weeks of the month and holds for various stock return indices. French (1980) conducted a study form 1953-1977 discovering a trend where average returns on S&P portfolios were negative on Mondays, nonetheless positive on the remaining weekdays (French, 1980). After French (1980) published this paper on the unusual stock returns on Mondays, multiple studies have confirmed the same effect both using different time periods and various stock return indices.

2.6.3 The Small Firm Effect

The theory of the *small firm effect*, also known as the "size effect" states that smaller firms or companies with relatively small market capitalization (less than $1 billion) tend to outperform larger companies (Roll, 1981) (NASDAQ, u.d.). Banz (1981), Reinganum (1981), among others, found that stock returns tend to be negatively associated with aggregate market values, referred to as “firm size”. When adjusting for risk, Banz (1981) discovered that small firms generate larger risk-adjusted returns compared to large firms. However, later studies have found the opposite, that stocks with large market capitalization generate higher returns (Malkiel, 2003). Hence, it is possible that the early reviews of the anomaly have suffered from bias, as recent studies have not been able to confirm the effect.

2.6.4 The Momentum Effect

Jegadeesh and Titman (1999) documented the existence of *the momentum effect* in stock prices. They found that securities with strong past performance tend to continue to do well, while for securities with poor past performance, prices keep falling (Jegadeesh & Titman, 1999). Other studies have later corroborated these findings where Rouwenhorst (2002) extended the study to twenty emerging markets, finding the same significant results, consequently proving the persistence of the momentum phenomenon. Contrary to this, other researchers have discovered "reversals" called *the contrarian effect*, the opposite phenomenon where past losers outperform past winners (Bondt & Thaler, 1985). Fama and French (1996) tested the two strategies by applying their three-factor model. While the contrarian effect proved to be insignificant, the model detected significant abnormal returns for past low returns and past high returns, supporting the momentum effect (Fama & French, 1996).

2.7 Behavioral Finance

Following the acknowledgment of the market anomalies came the blossoming of research on behavioral finance. That is, considering finance from a more extensive social science perspective, including both psychology and sociology. In the 1990s, substantial parts of the academic discussion shifted away from quantitative econometric analyses of time series on stock prices, towards investigating how human psychology and behavior relates to financial markets. The theoretical models were no longer viewed as sufficient to describe all the observed anomalies that occurred in the market.

The theory of behavioral finance has shown a contradicting view and challenged the efficient market hypothesis and its validity (Schiller, 2003). While the EMH does an excellent job of illustrating characterizations of an ideal world, the pure form fails in accurately explaining the dynamics of actual markets. Research on behavioral finance has found that individuals do not necessarily behave in the way said to be "rational" by classical economists, and thus can make the market inefficient (Peters, 2003). According to Fama (1965), the semi-strong form of the efficient market theory is dependent on all publicly available information being incorporated into market prices. The theory assumes that stocks are fairly and efficiently priced, and that investors act rationally as well as uniformly when valuing all available information. Hence, an investor is not able, on average, to earn returns above what is warranted for by the endured risk. The contribution of behavioral finance of investors being irrational contradicts this view and brings out deviations of asset prices from their fundamental values (Barberis & Thaler, 2003).

2.8 Earlier Findings

There has been conducted several studies on the phenomena of abnormal returns concerning announcements of mergers and acquisitions in stock markets around the world. Most studies on the area select either a specific industry to examine on a global basis or choose to investigate overall M&A within some given geographical boundaries.

The motivation and the form of takeover activity in various countries are affected by numerous institutional characteristics as well as differences in business systems (Georgen, Martynova, & Renneboog, 2005) (Hall & Soskice, 2001). In both the US and the UK, hostile takeovers have been common for a long time, and the M&A-level has been high. However, in both Japan and Continental European countries like France and Germany, M&A activity had rarely occurred before the 1990s. In these countries, hostile takeovers have for a long time been perceived as being impossible to implement. However, in later years M&A activity has increased globally, much due to several different legal changes (Jackson & Miyajima, 2007).

2.8.1 Global – Telecommunications

Park et al. (2002) examined how market participants reacted to M&A involving companies in the telecommunication industry. Using a sample of 42 deals in the period from 1997-2000 they found evidence of negative market reactions regarding the acquirer´s stock returns around the event's announcement date. The results indicate that cross-border M&A activities mainly drive the unfavorable response. This is consistent with the synergy trap hypothesis where managers are not able to adequately manage the acquisition process due to a lack of information about their targets (Park et al., 2002).

Olaf Rieck (2002) investigated value creation in international telecommunication acquisitions using the event study methodology. By including 72 cross-border acquisition deals within the telecommunications industry, he examined how the Cumulative Abnormal Returns (CAR) reacted to the announcement of M&A deals. He found that the overall impact of international telecom M&A created insignificant abnormal returns. Even though managers have a perception of M&A deals being easier to profit from after the deregulation of markets experienced since the late 1990s, Rieck´s study proved this to be inaccurate. However, the study showed that transactions are more likely to be successful when the acquirer is small, when the target is in a close geographical distance and when there are close economic ties between the acquirer and the target (Rieck, 2002).

In 2010, Olav Rieck published a new article on the same topic investigating M&A announcements of major telecommunication companies listed on either US or European stock exchanges in the period 1998-2007. Using three symmetric event windows and an estimation period of 120 days, he found significant support for the hypothesis that M&A activities positively impact participating firms (Rieck, 2010).

Through highlighting the finding suggesting bidders, with interesting exceptions, earn zero abnormal returns around the announcement date of a merger transaction, Bruner's study from 2014 compared and summarized evidence form 41 studies conducted in the period from 1971-1991. Out of the total sample, 20 of the studies reported negative abnormal returns, 13 being statistically significant. He concluded that the aggregate, abnormal returns to the shareholders of the acquiring firm are essentially zero (Bruner, 2002).

2.8.2 North America

Baker and Kiyamaz (2008) used the event study methodology to investigate responses associated with the announcement of large domestic M&A involving public US acquirers from 1989 to 2003. To identify underlying motives for engaging in M&A activity and examine potential determinants for abnormal returns, they partitioned the results by industry type. To measure abnormal returns, they applied the market model method to account for the risk associated with the market and mean returns. They found that the wealth effects of the acquirers range from being significantly negative to significantly positive, depending on the industry investigated. However, their empirical evidence shows that the bidding firm's announcement returns are on average significantly negative. Decisive factors for acquirers not succeeding with the deal includes the level of financial slack and to what degree the industry is regulated (Baker & Kiymaz, 2008).

Wilcox, Chang and Grover (2001) conducted an event study examining 44 M&A transactions involving 89 partners in the telecommunication industry following the 1996 Telecommunications Act. They tested multiple hypotheses relating to market valuation, near and far diversification and firm size. They found that announcements regarding M&A activities resulted in significant increases in the market value of the firms involved. Their findings were interesting as prior studies in the IT area found no significant movements in the stock price following such announcements (Wilcox et al., 2001). In addition, they found that deals, where the acquirer and the target were operating within related businesses, on average, yielded higher returns than those where the parties were involved in unrelated business areas. Furthermore, evidence from the report showed that in deals involving one large and one small firm, the small firm reaped the valuation benefit (Wilcox et al., 2001).

2.8.3 Europe

Campa and Hernando published an event study in 2004 looking at value creation from the announcement of M&A in the European Union in the period 1998-2000. The study was based on a sample of 262 M&A deals and used several event windows in the calculation of CAR. The results were inconclusive on the returns to bidding firms' shareholders. The overall evidence displayed an even distribution between either showing negative CAR or a slightly positive CAR. Conversely, the mean CAR to shareholders for acquiring firms was not significantly different from zero on the aggregate level. Nevertheless, returns to acquiring firms were negative in almost 55% of the transactions (Campa & Hernando, 2004).

These results are consistent with previous findings on M&A literature that reports zero or negative returns to acquiring firms (Bruner, 2002). In addition, they found that acquirers have a lower CAR in deals involving heavily regulated industries, although these differences are not always significant. This evidence is consistent with the perceived existence of various obstacles (e.g., cultural, legal and transactions barriers) to the successful conclusion of a merger (Bruner, 2002).

Goergen and Renneboog (2004) did an event study measuring the short-term wealth effects for large intra-European M&A by calculating the Cumulative Average Abnormal Returns (CAAR). The data sample consisted of 228 transactions in inter-European countries in the period 1993-2000. They found that acquirers' stock price had a slightly positive reaction with a significant announcement effect of 0.7 %. Furthermore, they found that the location of the bidder relative to the target had an important impact on the wealth effects, where UK deals generated significantly higher CAAR than their Continental European counterparts. In addition, they found substantial evidence that the means of payment had a large impact, where deals financed by solely cash triggered higher abnormal returns compared to all-equity funded transactions (Georgen & Renneboog, 2004). Hence, the evidence on European M&A transactions has proven to be inconclusive.

2.8.4 Asia

Empirical evidence shows that studies in several Asian markets including Japan, Hong Kong, China and India find either small negative or positive abnormal returns for the bidding firms engaging in M&A transactions. The common denominator between the studies found that return movements occurring at the announcement of the event were insignificant (Rani, Yadav, & Jain, 2013) (Anand & Singh, 2005).

Shah and Arora (2014) did an event study where they examined a sample of 37 public M&A announcements in the Asia-Pacific region from May 2013 to September 2013. By analyzing the CAAR through the market model, they found that acquiring firms did not show statistically significant returns across any of the selected event windows. Hence, they failed to reject the null hypothesis that CAAR were insignificantly different from zero at all levels of significance (Shah & Arora, 2014). The results from Shah and Arora's study are in line with several other studies including (Swaminathan, Murshed, & Hulland, 2008), (Papadatos, 2011) and (Franks, Harris, & Titman, 1991), and in contrast with researchers like (Wong & Cheung, 2009), (Rosen, 2006) and (Aintablian & Roberts, 2005).

Wong and Cheung (2009) investigated the wealth effects of M&A announcements in Asian bidding and target firms in the period 2000-2007. By applying the event study methodology, they calculated the stock price reaction in 658 different M&A transactions by using the market model. Most of the M&A activities from the sample occurred in Japan, Singapore and Hong Kong in the study period. They found that the CAAR of bidding firms were significantly positive around the time of the post-announcement period. The evidence suggests that the shareholders of Asian companies support M&A transactions (Wong & Cheung, 2009). However, potentially major differences in countries within the Asian region have to be taken into consideration when comparing results across nations in the area.

3.0 Methodology

This section presents the methodology applied in this paper's analysis of stock reactions caused by M&A announcements. First, we provide an introduction to the concept of event studies before explaining why and how we apply a six-step process, inspired by Henderson (1990) among others. Furthermore, we will present the models applied in our estimations of both normal returns, abnormal returns as well as cumulative abnormal returns. Last, various test statistics including both parametric and non-parametric tests are introduced. As a whole, this section will provide a foundation for understanding the methodology applied throughout the paper.

3.1 Event Study

Even though researchers have investigated M&A for decades, they lack *one* resolute instrument for measuring the effects of firm-specific and deal-specific determinants around M&A announcements. For this thesis, we have decided to apply an event study methodology similar to the ones conducted by MacKinley (1997) and Campbell, Lo and MacKinley (1997). Event studies investigate the "*abnormal return of companies before, during, and after a common type of event, where the goal is to analyze whether the event has any influence on the company's share price*" (Patricksson & Evans, 2016). Through empirical evidence, Duso, Gugler and Yurtoglu (2010) have proven the ability of event studies to capture M&A's ex-post profitability.

Event studies have several applications. Within finance, they have been applied to a variety of economy-wide and firm-specific events such as mergers and acquisitions, earnings announcements and issuing of new debt or equity (MacKinley, 1997). The history of event studies dates back to 1933 when James Dolley examined the price effects of stock splits (Dolley, 1933). Until the late 1960s, the sophistication of event studies increased, including improvements of separating out confounding events and removing general stock price movements. In the late 1960s, Ball and Brown (1968) and Fama, Fisher, Jensen and Roll (1969) introduced the methodology that is essentially the same as we use today.

According to Campbell et al. (1997), the idea behind the execution of an event study is to test whether the market is efficient as implied by the EMH; whether "*the market process the information surrounding an event in an efficient and unbiased matter*" (Patricksson & Evans, 2016). As we are examining a semi-strong form of the EMH by investigating event windows longer than one day, we will not test for complete market efficiency. However, the semi-strong form will allow us to control for information leakages prior to the event as well as investors' lagged response time to information (Patricksson & Evans, 2016).

3.2 Shortcomings of the Event Study Methodology

Although the methodology of event studies has been successful in the area of economics, finance and accounting since the late 1960s, there have been several limitations to its applications (Chen, 2017). First, event studies will be less useful in cases where the event date is difficult to identify precisely due to partial anticipation. This inference with event-study uncertainty ties to the abnormal returns within the event window not only being dependent on the valuation effect but also on the relation between firm characteristics and the extent to which the market anticipates the event. Investors can rationally use firm characteristics to forecast the likelihood of the event happening (Campbell et al., 1997). This introduces a selection bias, where the assumption that the regression residual is uncorrelated with the independent variables is violated. Hence, the *Ordinary Least Squares* (OLS) estimators technically become inconsistent. Nevertheless, Acharya (1988) and Eckbo, Maksimovic and Williams (1990), among others, provide examples where consistent variables can be provided by explicitly allowing for selection bias (MacKinley, 1997) (Campbell et al., 1997).

Second, there is the issue about the role of the sampling interval that considers the potential gains from applying shorter intervals. Campbell et al. (1997) state that the ability to statistically identify the effect of the event will increase with shorter sampling intervals, with the condition of knowing the timing of the event precisely. This is due to the variance of the abnormal returns being reduced without having to change the mean (Campbell et al., 1997). Hence, using daily stock return data will lead to an increased explanatory power than obtained through the use of monthly data (MacKinley, 1997).

Other possible biases can arise in the context of conducting an event study. The nonsynchronous trading effect appears when prices seem to be recorded at one-length time intervals despite possible being registered at irregular lengths (Campbell et al., 1997). Thus, when applying *closing prices* for daily returns, the returns' intervals cannot be ensured equally spaced at 24-hours intervals. This naturally imposes a bias in the market model beta. Nevertheless, for actively traded stocks the potential adjustment is proven to be small and unimportant (Scholes & Williams, 2002).

Lastly, deviations from the assumption that "*returns are jointly normal and temporally independently and identically distributed*" (MacKinley, 1997) can lead to biases. The premise of normality is essential for the finite sample to hold. In the absence of this assumption, the results will be asymptotic. However, this has proven to be a minor issue in the context of event studies. As for the test statistics the convergence to the asymptotic distribution is relatively quick.

3.3 Why a six-step process?

Previous literature has defined event studies as consisting of a series of steps. However, the classification of each step, as well as the number of steps, differs across researchers. Below, we present a summary of different steps applied in papers similar to ours (Table 3.1). A more extensive summary can be found in Appendix 1.

# of steps	Steps	Source
7	1. Event definition 2. Selection criteria 3. Normal and abnormal returns 4. Estimation procedure 5. Testing procedure 6. Empirical results 7. Interpretation and conclusion	Campbell, Lo and MacKinley (1997)
5	1. Define event date 2. Characterize normal returns 3. Calculate excess returns 4. Aggregate excess returns 5. Run statistical tests	Henderson (1990)
3	1. Identify relevant transactions 2. Calculate cumulated abnormal returns 3. Test statistical significance of CARs	Kirchhoff and Schiereck (2011)
4	1. Cleaning data and calculating the event and estimation windows 2. Estimating normal performance 3. Abnormal and cumulative abnormal performance 4. Test for significance	Data and Statistical Services (2007)
5	1. Identify the event of interest 2. Model the security and price reaction 3. Estimate the excess returns 4. Organize and group excess returns 5. Analyze results using statistical significance tests	Bouwman (1983)

Table 3.01: A selection of various steps applicable in conducting an event study

Considering the different approaches to conduct an event study, we believe that the method of Kirchhoff and Schiereck (2011) ignore the importance of specifying the method for estimating normal returns and how abnormal returns are calculated. Furthermore, both Campbell et al. (1997) and Data and Statistical Services (2007) include either normal and abnormal returns or abnormal returns and cumulative abnormal returns in

the same bullet point (Campbell et al., 1997). We believe that this structure will make the analysis messy, giving a poor overview of the process.

By comparing and combining elements motivated by the steps of Henderson (1990), Bowman (1983) and Campbell et al. (1997) we ended up with the following six-step process:

1. Determine and validate the event and event date
2. Define selection criteria
3. Calculate normal returns
4. Estimate abnormal returns
5. Aggregate abnormal returns
6. Test for statistical significance

We believe that following the above-mentioned steps is consistent with previous literature and will ensure the thesis is easy to follow. In the next section, we will discuss each step in detail to provide some further insight.

3.4 The six-step event study process

3.4.1 Determining and validating the event and event date

According to Henderson (1990), "*misidentification of an event can obscure an issue*". Further, he indicates the importance of this step by referring to earlier studies being unable to find significant and consistent results when looking solely at the date of the merger (Henderson, 1990). However, he finds that by applying longer event windows one can decrease the uncertainty that appears when the researcher has to pinpoint an exact time of the event. Hence, the event window could either be set to the day of the announcement or be expanded to include both days before and after the event date. This is consistent with the study of Shah and Arora (2014), who state that usually, event windows of M&A announcements are chosen to include a few days before and after the announcement itself. They emphasize this fact by pointing out that these studies try to analyze the violation of the efficient market hypothesis (Shah & Arora, 2014). While the pre-event period is included to control for any leakages of information prior to the event, the post-event period allows for the inclusion of any effect potentially delayed by disseminated information (Peterson, 1989).

3.4.2 Defining Selection Criteria

When deciding which deals and companies to include in the study, we have considered several selection criteria. First, the data of each transaction has to be available in databases we have access to. In addition, the companies' historical data, such as daily stock data and various annual fundamental figures must be available for us to include the company in the sample. The data selection and its criteria will be discussed further in Section 4, *Sample and Data*.

3.4.3 Calculating normal returns

The next step of the event study process is to decide which approach to apply when estimating normal returns of the stocks. There are several different models available for measuring normal performance. Even though the economic Capital Asset Pricing Model (CAPM) used to be the dominant model, statistical models like the Market Model (MM) and the Constant Mean Return Model (CRM) have become the two primary methods for estimating normal returns in modern research. The main difference between the two statistical models is that the MM assumes a linear relationship between the stock's return and the market's return, while CMR implies that the mean return of a given stock is constant through time (MacKinley, 1997).

3.4.4 Estimating abnormal returns

The measure of abnormal returns is crucial in the following process of identifying the effects of the event. According to Kirchhoff and Schiereck (2011), abnormal returns are the "*deviation of the actually observed stock returns from the theoretically expected stock returns*". Hence, subtracting the normal return of the stock over the event window from the actual return over the same event window will give us the abnormal return.

3.4.5 Aggregating abnormal returns

To be able to give an interpretation of the overall results of M&A transactions' impact on stock prices, every single deal-specific abnormal return has to accumulate into one. As most researchers use cumulative abnormal returns as their estimator, using the same measure will enable us an easier comparison of our results to those in previous empirical findings.

3.4.6 Testing for statistical significance

To be able to validate the effects of abnormal returns, as well as the variables affecting abnormal returns, statistical tests are necessary. There are numerous possibilities of verifying the results of an event study. It can be done through either parametric (e.g., student's t-test and multiple regressions) or non-parametric

tests (e.g., sign test and rank test). According to Cowan (1992) and Dutta (2014), applying parametric tests is currently the most popular way to investigate the significance of the different variables in an event study, while non-parametric tests are usually used as a complement (Sheskin, 2013).

3.5 Models for measuring normal performance

The selection of an appropriate normal return model is an essential part of an event study as it relies on capturing any abnormal returns. This is done by comparing the difference between actual and normal returns. The normal return of a security is the estimated return in the absence of the event, which in this thesis is the absence of the merger announcement. Correct specification of the normal return is crucial to obtain robust and valid results (Strong, 1992).

According to MacKinley (1997), there are several models available for calculating the normal performance of a security. Overall, the models are separated into two groups, statistical and economic models. Statistical models consider the behavior of security returns and do not take into account any economic arguments. The economic models depend on assumptions regarding investor behavior and do not base the estimation solely on statistical assumptions.

3.5.2 Statistical Models

3.5.2.1 Constant Mean Return Model (CMR)

The Constant Mean Return Model assumes that the expected return on assets can differ across companies but is independent and identically distributed with a constant mean and variance over time (time-invariant) (Zivot, 1998). The model is:

$$R_{i,t} = \mu_i + \epsilon_{i,t} \tag{1}$$

$$E[\epsilon_{i,t}] = 0 \qquad VAR[\epsilon_{i,t}] = \sigma^2_{\epsilon_i} \tag{2}$$

Source: (MacKinley, 1997)

$\mathbf{R_{i,t}}$ = return for stock i in period t

$\boldsymbol{\mu_i}$ = mean return for asset i

$\boldsymbol{\varepsilon_{i,t}}$ = disturbance term for stock i in period t

According to Brown and Warner (1980, 1985), the Constant Mean Return Model is considered the simplest and highest restrictive model regarding the estimation of normal performance. However, they state that results based on this model do not systematically deviate from results from more sophisticated models. This lack of sensitivity attributes to the fact that the variance of abnormal returns is not considerably reduced by selecting a more advanced model (MacKinlay, 1997).

3.5.2.2 Market Model (MM)

The Market Model has the assumption of a linear and constant relation between the return on each individual asset and the return of the market index. According to Strong (1992), the Market Model is the most frequently applied model in the estimation of expected returns (Cable & Holland, 1999). For any security, the Market Model is:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \epsilon_{i,t} \tag{3}$$

$$E[\epsilon_{i,t}] = 0 \qquad VAR[\epsilon_{i,t}] = \sigma^2_{\epsilon_i} \tag{4}$$

Source: (MacKinley, 1997)

$R_{i,t}$ = return for stock i in period t

$R_{M,t}$ = return on the market portfolio in period t

α_i, β_i and σ_i^2 = parameters for the market model regression (OLS)

$\epsilon_{i,t}$ = disturbance term for stock i in period t

When calculating the return on the market portfolio the market model applies a broad-based stock index, with the S&P 500, the CRSP Equal Weighted and CRSP Value Weighted indices being frequently employed. The Market Model offers improvements compared to the CMR as it removes a portion of the return related to variation in the market's return. As a result, the variance of the abnormal returns shrinks. In turn, this feature of the model can help detect effects around the announcement date (MacKinley, 1997).

Furthermore, the level of the coefficient of determination, R^2, will be able to determine whether it is beneficial to apply the Market Model. When R^2 increases, the variance of the abnormal returns declines, and the gain expands (MacKinley, 1997). Additionally, the superior significance of the regression (shown by the significance of the F-statistic) reflects the propriety of using the market model to calculate normal performance (Campbell et al., 1997).

According to a study conducted by Cable and Holland (1999), there is a robust preliminary preference in favor of the Market Model, which outperforms the CAPM (Cable & Holland, 1999). Furthermore, Brown and Warner (1985) found that methodologies based on the OLS market model are well specified under multiple conditions, which reinforces the conclusions from their earlier work. Hence, the market model proves to be a highly sufficient tool when calculating normal daily returns in the event study methodology.

3.5.2.3 Other Statistical Models

Numerous statistical models have evolved to measure normal returns on a security. A well-known version of statistical models is the *factor model*, motivated by its ability to reduce abnormal returns data's spread by explaining more of the variance in the normal returns. The Market Model is an example of a factor model with only one single factor. One could also apply the multifactor models that use several factors (e.g., size factors, book-to-market values, industry indices) in their computations. By comparing two or more factors, they can study relationships between variables and their performance. However, empirical evidence implies that the gains of adding more explanatory variables are limited. This due to the marginal increase in explanatory power by adding other factors than solely the market return factor. Hence, the reduction of variance in the abnormal returns will be small (MacKinley, 1997).

3.5.3 Economic Models

When applying economic models for measuring normal performance, various statistical assumptions must be imposed. However, the economic models are not solely based on these assumptions but also include economic restrictions. Hence, potential advantages can occur when choosing a model that enables estimation of more accurate measures of a constrained normal return (MacKinley, 1997). The Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT) both enforce such restrictions.

3.5.3.1 Capital Asset Pricing Model

Sharpe (1964) and Lintner (1965) define the CAPM as an equilibrium theory where the expected return of a security is decided by its covariance with the market portfolio. According to the CAPM, the expected return for security *i* is given by

$$E[R_{i,t}] = r_f + \beta_t(E[R_{m,t}] - r_f) \tag{5}$$

$$\beta_i = \frac{Cov(R_i, R_{mkt})}{SD(R_{mkt})^2} = \frac{SD(R_i) \cdot Corr(R_i, R_{mkt})}{SD(R_{mkt})} \tag{6}$$

Source: (Berk & DeMarzo, 2013)

$E[R_{i,t}]$= expected return on stock i at time t

r_f = risk free rate

β_i = firm-specific beta for firm i

$E[R_{M,t}]$ = expected return on the market portfolio in period t

In the 1970s, applying the CAPM in event studies was the common norm. Since then, researchers have discovered that multiple deviations occur when imposing economic restrictions on the market model, questioning the CAPM's validity. The findings of this potential sensitivity to the CAPM's restrictions have challenged the model's existence in research. This is due to the existence of the unrestricted market model, which eliminates this inherent sensitivity (MacKinley, 1997). Furthermore, Fama and French (2004) find that the empirical record of the CAPM invalidates its results. They state that the problem does not lie in the assumption of rational prices but is due to a violation of the CAPM assumptions (Fama & French, 2004).

3.5.3.2 The Arbitrage Pricing Theory

According to Ross (1976), the APT is an asset pricing theory where the expected return of a security is determined by its covariance with a linear combination of several risk factors, in the absence of asymptotic arbitrage. The APT is illustrated by the following equation:

$$E[r_i] = r_f + \beta_{i1} \cdot RP_1 + \cdots + \beta_{iK} \cdot RP_K \quad (7)$$

Source: (Berk & DeMarzo, 2013)

R_f = risk-free rate

β_{iK} = stock i's sensitivity to factor k (factor beta)

RP_k = risk premium for bearing the "factor k risk"

The APT is perceived as an alternative to the CAPM. However, the model applies the expected return on the risky asset and the risk premium of multiple macroeconomic factors (Ross, 1976). According to MacKinley (1997), general findings impose that the most crucial factor of the APT model is the market factor, while additional factors add relatively low explanatory power. Thus, similarly to other multifactor models, the gains of applying the APT instead of the market model are small. The main advantage brought forward by the APT model is its ability to eliminate the biases introduced by the CAPM. Nevertheless, as the statistical models have the same ability, such models are the dominant choice for conducting event studies (MacKinley, 1997).

3.6 Choice of model for normal performance

Based on the strong empirical support of the success of applying the market model in event studies, using this model when calculating the normal returns appears as the most rational choice. According to Campbell et al. (1997), "*there seems to be no good reason to use an economic model rather than a statistical model in an event study*". Regardless of the simplicity of the constant mean return model compared to the market model, the fact that nearly all of the similar research papers, (MacKinley, 1997) (Moeller et al., 2004) (Dilshad, 2013) applies the market model, gives us reassurance that this is the correct choice. In the following sections on abnormal returns and cumulative abnormal returns, the market model is used as the normal performance return model.

3.7 Selection of market index

As mentioned, the market model has the assumption of a linear and constant relation between the return on each individual asset and the return of the market index. To use the market model, we need to specify which market index to use for each firm. To determine this, we run five regressions for each firm, where we regress the daily returns of each firm against the daily returns of five different indices. These five indices are: MSCI World, S&P Global 1200, S&P Global 1200 Telecom, NASDAQ Telecom and the main index the respective firm is listed on (denoted by X in the regressions below). By including more than one index, we are able to test the significance of different indices, and eventually choose the best one (Campbell et al., 1997). We will use a standard OLS regression and perform the following set of regressions:

$$R_{it} = \alpha_{iMSCI\ WORLD} + \beta_{iMSCI\ WORLD} R_{MSCI\ WORLDt} + \varepsilon_{it}$$

$$R_{it} = \alpha_{iS\&P\ GLOBAL\ 1200} + \beta_{iS\&P\ GLOBAL\ 1200} R_{S\&P\ GLOBAL\ 1200t} + \varepsilon_{it}$$

$$R_{it} = \alpha_{iS\&P\ GLOBAL\ 1200\ TELECOM} + \beta_{iS\&P\ GLOBAL\ 1200\ TELECOM} R_{S\&P\ GLOBAL\ 1200\ TELECOMt} + \varepsilon_{it}$$

$$R_{it} = \alpha_{iNASDAQ\ TELECOM} + \beta_{iNASDAQ\ TELECOM} R_{NASDAQ\ TELECOMt} + \varepsilon_{it}$$

$$R_{it} = \alpha_{iX} + \beta_{iX} R_{Xt} + \varepsilon_{it}$$

$R_{i,t}$ *= return on stock i at time t*

α_i and β_i *= coefficients provided by running the OLS regressions*

$\varepsilon_{i,t}$ *= error term of stock i at time t*

X *= main stock index each company is listed on*

After each set of regressions, we compared the results by checking three different factors: (1) The F-statistic, which expresses the overall significance of the model, (2) R-squared, which represents the explanatory power of the model, and (3) the significance of the beta coefficients, indicated by the t-statistics. By using the factors above, we first chose the models with the highest significance. In cases where several models were equally significant, we chose the model with the highest R-square. In some situations, two models were equally significant and had the same R-square, in which case we chose the models with the most significant Beta variable. See *Appendix 2* for the output from two of these regressions. Not all outputs are included as the same procedure was followed for all firms. Based on the selection criteria above, we chose the main index the firms were listed on for 49 of the 72 firms. The other 23 firms were distributed across the other four indices with three on MSCI World, five on S&P Global 1200, eight on Nasdaq Telecom and seven on S&P Global 1200 Telecom.

3.8 Measuring Abnormal Returns

The estimation of the abnormal returns examines stock returns around the announcement date and separates out the portion of the total return explicitly caused by a reaction to the event. Thus, even though parts of the total return results from volatility in the overall stock market, the remainder reflects the specific event analyzed. Hence, estimation of the abnormal returns is done by subtracting out returns attributable to overall stock market movements (Schweitzer, 1989). As for the normal returns, the estimation of the abnormal returns is a crucial part of the analysis. This because abnormal returns are the measure of the impact of the occurring event (Campbell et al., 1997).

The simplest specification of abnormal returns is calculated by subtracting the estimated normal returns from actual returns:

$$Abnormal\ Return = Actual\ Return - Expected\ Return \tag{8}$$

The movements, if any, in the abnormal returns will reflect the impact of the event (Schweitzer, 1989). Considering the semi-efficient market hypothesis, we expect the abnormal returns to reflect the impact of the event. In the absence of the event, the theoretically expected stock price should equal the observed share price. Thus, the specification of the abnormal return provided by the equation should represent the true abnormal return obtained (Berk & DeMarzo, 2013). Therefore, the abnormal return (AR) is:

$$AR_{i,t} = R_{i,t} - E\left[R_{i,t}\middle|X_t\right] \tag{9}$$

$AR_{i,t}$ = abnormal return at time t for firm i

$R_{i,t}$ = actual return at time t for firm i

$E[R_{i,t}]$ = expected return at time t for firm i

X_t = conditioning information for the normal return model (represented by the market model)

The abnormal return of a security is therefore dependent on the calculation of the normal return (calculated by the Market Model). The Market Model enables the prediction of the return of the stock in the absence of the event. The model builds on the actual return, as well as the correlation of the stock to a reference market. Formally, the equation according to the Market Model is:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t}) \tag{10}$$

Hence, the abnormal return on a given day within the event window represents the distinction between the actual return ($R_{i,t}$) and the normal return. The figure is predicted by (1) the relationship between the stock and its reference index (expressed through the regression parameters α and β) and (2) the actual reference market's return ($R_{m,t}$). This method is applied as it reflects the market's future expectations of firm performance resulting from an event. Besides, the market model is considered the most frequently employed model for detecting and analyzing abnormal returns resulting from events (Pellicer & Rees, 2010). To calculate the abnormal returns on each deal, we apply the formula above to the respective event windows and estimate the daily abnormal return for each deal.

3.9 Cumulative Abnormal Returns

To be able to draw overall inferences for the event of interest, aggregation of the abnormal returns is necessary. This can be done along two dimensions - across stocks and through time (Campbell et al., 1997) (MacKinley, 1997). Since this thesis investigates the effects of M&A announcements on the acquirer, we will focus on the time dimension. However, we recognize the possibility of doing an event study with the security-dimension if investigating the impact of industry-wide effects.

To accommodate a multi-period event window, we consider the Cumulative Abnormal Return (CAR). The CAR (t_1,t_2) is the sample cumulative abnormal returns from period t_1 to t_2 where both lies inside the event window ($T_1 < t_1 \leq t_2 \leq T_2$) and is the sum of the included abnormal returns (MacKinley, 1997).

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{11}$$

Hence, the CAR for stock *i* is the sum of the abnormal returns between period t_1 and t_2. The null hypothesis that "*the event has no impact on the distribution of the return*" (MacKinley, 1997), can be tested under this H_0 distribution of cumulative abnormal returns:

$$CAR_i(t_1, t_2) \sim N\left(0, \sigma_i^2(t_1, t_2)\right) \tag{12}$$

In the case of having more than one event observation at the same date, the abnormal return would require aggregation not only across the time dimension, but also across stocks. We would then have to make an assumption of no clustering. Thus, the events in the sample should not be overlapping. Imposing this constraint makes the CARs independent across stocks (MacKinley, 1997). Defining T_1 as the last day of the estimation window and T_2 as the last day of the event window, we can use equation (11) for each event period, t = T_1+1,…, T_2 to aggregate the individual stock's abnormal returns. The sample average abnormal return for period t, given N events at the given day, is

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \tag{13}$$

Furthermore, the cumulative average abnormal return can be calculated for any time interval in the event windows as

$$CAAR_{t_1,t_2} = \sum_{t=t_1}^{t_2} AAR_t \tag{14}$$

However, we have already dealt with the clustering issue by manually removing all overlapping events. Hence, the cross-sectional correlation among abnormal returns that appear when the event day is the same for sample firms is removed. For this reason, the N in formula (13) equals one. Thus, aggregating across the dimension of the observations is proven unnecessary.

In addition to evaluating the method of CAR, we also have to acknowledge the other method of buy-and-hold abnormal returns (BHAR). BHAR is defined as the "*difference between the realized buy-and-hold return and the normal buy-and-hold return*" (Barber & Lyon, 1996). Barber and Lyon (1997) emphasize the advantages of BHAR versus CAR. Unlike CAR, BHAR includes the effect of compounding when applying monthly returns and provides less biased estimates for the accumulated abnormal returns (Barber & Lyon, 1997). However, BHAR is by most researchers favored when investigating larger time intervals, but not for daily returns (Barber & Lyon, 1997) (Henderson, 1990). In addition, most researchers of similar studies still use CAR in their analysis. Hence, choosing CAR as the measure of abnormal returns will enable us to easier compare our results to those of other papers.

3.10 Test Statistics

To validate the effects of variables defined on abnormal returns, the statistical significance of the returns against the independent variables must be tested. Hence, to interpret the results from an event study, we need to be able to identify the potential presence of non-zero abnormal returns. These tests help to detect the presence of abnormal returns within each individual event window. There are various types of test statistics examining the consistency of the sample data to check whether the null hypothesis should be accepted or rejected. In the field of short-term event studies, several test-statistics have been developed and can be separated into two groups: parametric and non-parametric tests. The main difference between the two groups is that the parametric tests rely on an assumption concerning return distribution, while non-parametric tests make no such assumptions (MacKinley, 1997). According to previous literature, non-parametric tests serve as a tool to support the results initiated by the parametric tests and thereby increase its reliability (MacKinley, 1997) (Brown & Warner, 1985).

According to Henderson (1990), it is necessary to consider several assumptions when applying econometrics in an event study:

1. Residuals are normally distributed with a mean of zero
2. Residuals are not serially correlated
3. Residuals have constant variance and are therefore homoscedastic
4. Residuals are not correlated with the explanatory variable
5. There is no correlation between the residuals of different events

Source: (Henderson, 1990)

The first assumption mentions that the residuals are normally distributed with a mean of zero. However, stock returns prove to violate this assumption. The econometric problem is even more troublesome for daily returns, which is an increasingly popular data frequency applied in event studies (Henderson, 1990). Later, Berry, Gallinger and Henderson (1990) replicated a review of Brown and Warner (Brown & Warner, 1985), showing that the residuals or prediction errors based on the OLS market model regressions proved to be more normal. Using a more powerful normality test, Berry et al. (1990) concluded that the residuals in regressions of stock returns are normally distributed. The nature of this residual distribution indicates that parametric tests are generally preferable to non-parametric ones (Berry et al., 1990).

The second assumption that the residuals are not serially correlated can potentially pose a threat, as there is evidence of slight serial correlation in security returns (Henderson, 1990). Stock trading could be nonsynchronous in the sense that different stocks have different trading frequencies where the intensity of trading varies from hour to hour. When applying daily stock returns, we use the stock's *closing* price, introducing the assumption that returns are an equally spaced time series with a 24-hours interval, potentially creating bias. This induces a bias in the beta of individual stocks where betas of less frequently traded stocks will have a downwards bias. However, Henderson concludes by stating that "*autocorrelation in the residuals is even smaller and appears to pose little problem for event studies*" (Henderson, 1990). Regardless of the conclusion, it is crucial to control for the possibility of autocorrelation. This could be done by running a Durbin-Watson test and/or a Breuch-Godfrey test for autocorrelation. The results of these tests will be displayed in Section 6, *Results*.

The third assumption states that residuals have a constant variance, thus assuming they are homoscedastic. However, empirical evidence proves that variance shifts coincident with financial events (Beaver, 1968) (Patell & Wolfson, 1979). Berry et al. (1990) revealed significant variance non-consistency in the returns data through an F-statistic of heteroscedasticity. To ensure that the dataset consists of heteroscedastic standard errors, we run both a White test and a Breush-Pagan test. Should these tests prove the residuals to vary, we will control for heteroscedasticity by using heteroscedasticity consistent standard errors when running our OLS-regressions. The results of these variance-tests will be presented in Section 6, *Results*.

The fourth assumption mentions that the residuals are not correlated with the explanatory variables. However, evidence shows a correlation between the residuals and the independent variables' return on the market index, R_m . Berry et al. (1990). Although the market model requires the use of the market return to calculate the expected return, the market return is not treated as an independent variable. Furthermore, we

include the external variables *Merger waves, Interest rate* and *GDP* in the OLS-regressions to control for market movements. Lastly, we do not consider this assumption as an issue, as the telecom industry deviates from the total market movement pattern over time. Hence, the market return should not be vastly correlated with the residuals.

The final assumption discusses the correlation between the residuals of the different events. Henderson (1990) and Woolridge (2009) discuss this absence of calendar clustering in their studies where "*events [are] occurring at or near the same time*" (Henderson, 1990). As mentioned, this is controlled for by manually excluding overlapping events by removing events that occur within the estimation window and/or event window of an already occurring event.

3.10.2 Parametric tests for significance

Parametric tests in event studies enable the researchers to evaluate differences of means at a specified time. Thus, testing abnormal return for a specific day (i.e., the announcement day) or cumulative abnormal return, evaluating the entire event window. The parametric tests assume that the returns are normally distributed and that the sample data is cross-sectional and independent for a specified population (Martens, Pugliese, & Recker, 2017). In this paper, two different parametric tests will be applied to explain the reaction followed by a merger announcement.

First, we will describe and apply the student's t-test for AR and CAR, following a normal distribution. If the results show that the null hypotheses, AR = 0 and CAR = 0 cannot be rejected, it can imply that the market has expected the merger or the acquisition. However, the rejection could also indicate that the expectations of the market were initially unrealistic and that the market is inefficient. Second, we will apply a multiple regression model, which is an extension of the single variable OLS model. Our main motive for this particular choice is to determine which, if any, of our deal-specific and firm-specific variables affect abnormal returns during an M&A announcement.

3.10.2.1 Testing the significance of AR and CAR

Qureshi, Abdullah and Imdadullah (2012) and several other researchers apply the t-test statistic to test the null hypothesis "*Average abnormal return on any day in the event window is equal to zero*". The t-statistic is a figure that shows the ratio between the abnormal return on security *i* on a given day *t* to its standard deviation. As illustrated by Campbell et al., (1997), the t-tests are applicable for the aggregated form of both AR and CAR.

First, we will test the significance of the abnormal returns in every day of the respective event windows, where the null is as follows; $H_0 = AR_{i,t} = 0$ and the alternative hypothesis $H_A = AR_{i,t} \neq 0$.

$$t_{AR_{i,t}} \frac{AR_{i,t}}{S_{AR_i}} \tag{15}$$

$$S^2_{AR_t} = \frac{1}{M_i - 2} \sum_{t=T_0}^{T_1} (AR_{i,t})^2 \tag{16}$$

S_{Ari} = standard deviation of the abnormal returns in the event window

M_i = number of non-missing returns

If the null hypothesis is accepted, the t-test has proven to follow a student distribution with degrees of freedom equal to (n-1) where n equals the number of observations. The value of the t-statistic indicates the direction of the correlation. Hence, a positive t-value suggests a positive relationship between the ARs or, conversely, a negative relation. The significance is detected by comparing the t-value with the critical value at a 1%, 5% and 10% significance level. If the t-value exceeds the critical value, the correlation is significant.

Second, the significance of the cumulative abnormal returns will be tested with a similar null hypothesis; H_0: $CAR_i = 0$ and the alternative hypothesis H_A: $CAR_i \neq 0$.

$$t_{CAR_t} \frac{CAR_t}{S_{CAR}} \tag{17}$$

$$S^2_{CAR} = L_2 S^2_{AR_t} \tag{18}$$

S_{CAR} = standard deviation of the cumulative abnormal returns

L_2 = T_2- T_1

T_1 = the latest day of the estimation window

T_2 = the latest day of the event window

The appropriate significance levels in this paper, with their associated critical values, are presented in the below Table 3.2. The t-test related to CAR is utilized to measure whether there is any change in AR during

the event window due to merger announcements.

Significance Level	Critical Value	# of stars
1%	2,576	***
5%	1,96	**
10%	1,645	*

Table 3.02: Critical values for different significance levels

3.10.2.2 Validating the effects of independent variables on abnormal returns

According to Stock and Watson (2015), the multiple regression model "*permits estimating the effect on Y_i while changing one variable (X_{1i}) while holding the other regressors (X_{2i}, X_{3i} and so forth) constant*". Including more independent variables minimizes the squared differences of all variables from the best-fit line, illustrating a relationship between the dependent and independent variables that will hold for the average population. Hence, by choosing this parametric model, we aim to minimize the amount of data left out and thus cover as much of the relationship as possible. However, when applying a multiple regression model, the probability of multicollinearity increases, and we will most likely not be able to find a perfect replication of the relationship (Stock & Watson, 2015). Regardless of its weaknesses, we believe that the model will capture the effect of the different dependent variables on the abnormal returns and provide us with interesting results.

Stock and Watson (2015) define the multiple regression model as:

$$Y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i \tag{19}$$

Y_i = observation of the dependent variable

X_{ki} = explanatory variables

ε_i = error term

β_0,…, β_k = parameters of interest, representing the relationship between the dependent variable and explanatory variables.

The population regression line, or "*the relationship that holds between Y and the X's on the average population*" (Stock & Watson, 2015) is

$$E(Y|X_{1i}) = x_1, X_{2i} = x_2, \ldots, X_{ki} = x_k = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \tag{20}$$

Furthermore, we want to use the OLS for multiple regressions to "*minimize the sum of square prediction mistake*" (Stock & Watson, 2015). Put differently; the objective is to calculate the OLS estimators $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k$, which implies "*the values b_0, b_1,…, b_k that minimize the sum of squared prediction mistakes*" (Stock & Watson, 2015). Arithmetically, the estimators and its predicted values and residuals are

$$\sum_{i=1}^{n}(Y_{i-}b_0 - b_1X_{1i} - \cdots - b_kX_{ki})^2 \tag{21}$$

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1X_{1i} + \cdots + \hat{\beta}_kX_{ki} \qquad and \qquad \hat{\varepsilon}_i = Y_i - \hat{Y}_0 \tag{22}$$

Additionally, there are three more assumptions to OLS than the five assumptions discussed by Henderson (1990) above:

1. $(X_{1i},X_{2i},\ldots,X_{ki},Y_i)$ i=1,…,n are independently and identically distributed
2. Large outliers in the dataset are unlikely
3. Perfect multicollinearity should not exist in the data

Before running the multiple regression, we control for the events being independently and identically distributed (i.i.d.) by selecting them randomly, based on specific criteria, as well as excluding overlapping events. In addition, we carefully choose which variables to include by checking their pairwise correlation, with the aim of removing potential multicollinearity.

Furthermore, we apply the stepwise algorithm in R, "stepAIC" as a tool when choosing which variables to include in the different multiple regression models. The Akaike Information Criteria (AIC) has two components; (1) a bias correlation factor (increases as you add more model parameters) and (2) a negative log-likelihood (estimates the lack of model fit to the observed data). The method is based on a mathematical algorithm and has its weaknesses as they do not take into account human emotions and the perspectives relating to behavioral finance. However, it provides a method of drawing an inference from several models simultaneously (Johnson & Omland, 2004). Yamashita, Yamashita and Kamimura (2007) studies show that "*there are more reasons to use the stepwise AIC method than the other stepwise methods for variable selection since the stepwise AIC method is a model selection method that can be easily managed and can be widely extended to more generalized models and applied to non-normally distributed data*". The exclusion done by the stepwise algorithm creates a starting-point in which explanatory variables to include in the different regressions for all individual event windows. Since stepAIC solely chooses variables based on

mathematical calculations, we force it to select some variables we would like to include in all the regression models. We choose to include all the deal-specific variables since these are widely discussed in previous research, and we would therefore like to investigate whether we can find similar effects in our sample. By doing this, we overcome some of the weakness of lacking human emotion in the method, and simultaneously include insights gained from previous literature and the interview with Einar Bjering.

3.10.3 Non-parametric tests for significance

As previously discussed, the inherent non-normal nature of daily stock returns may suggest the use of non-parametric tests for significance (Brown & Warner, 1985) (Berry et al., 1990). As non-parametric tests are free of the assumption of returns following a normal distribution, they are more robust at detecting the null of no abnormal returns that are false (Dutta, 2014). By reviewing multiple parametric and non-parametric tests, Dutta (2014) concludes that "*nonparametric sign and rank tests are well specified and have more power than the standard parametric approaches in detecting the short-run anomalies*". Hence, we will apply non-parametric tests to validate the parametric results.

In this paper, we will use the Sign test (Cowan, 1992) to confirm our parametric results on the abnormal returns. To check the robustness of the results of our independent variables applied in the multiple regression analysis, we will perform a Kruskal-Wallis H-Test.

3.10.3.1 The Sign Test

According to Dutta (2014), the sign test "*refers to a simple binomial test of whether the frequency of positive abnormal residuals equals 50%".* Before running the test, we need to determine the proportion of stocks in the sample having a positive abnormal return with the null hypothesis of no abnormal performance. The test requires that AR is independent across stocks and that the expected portion of positive abnormal returns equals 0.5 (Campbell et al., 1997). Accordingly, the null should not differ significantly from 0,5, thus $H_0 = p \leq 0.5$. The alternative hypothesis is $H_a = p > 0.5$, where $p = Pr(AR_i \geq 0$. Cowan (1992) defines the non-parametric test statistic for the sign test as:

$$t_{sign} = \sqrt{N}\left(\frac{p - 0.5}{\sqrt{0.5(1 - 0.5)}}\right) \tag{23}$$

where p is the observed fraction of the number of observations with positive abnormal returns against the total number of cases. Even though the test provides useful features for robustness checks, it has its

drawbacks. One disadvantage being that daily data on abnormal returns is skewed, resulting in the test being poorly specified (Campbell et al., 1997).

3.10.3.2 The Kruskal-Wallis Test

To validate the robustness of our parametric multiple regression analysis, we will run a non-parametric test on the different subsets of our dataset. To do this, we will apply the Kruskal-Wallis H test (KWH) that is a "*rank-based nonparametric test that can be used to determine if there are statistically significant differences between two or more groups of an independent variable*" (Lærd Statistics, u.d.). Through this test we can determine whether the factors affecting CAR across geographical regions were just the result of the regions merely yielding different CARs, or if it is actually a result of various factors affecting abnormal returns across different regions. According to Vargha and Delaney (1998), this test is the preferred procedure for comparing more than two independent samples.

The advantage of the model compared to parametric multiple regressions is that it does not assume normality. Applying the KWH test requires the following three assumptions to be made:

1. The dependent variable must be either continuous or ordinally measured
2. The independent variable should be grouped into two or more independent and categorical groups
3. The observations should be independent

Source: (Lærd Statistics, u.d.)

With the exception of assumption number one, these assumptions have already been controlled for. However, the cumulative abnormal returns are continuous in nature. Thus, eliminating any issues associated with assumption one.

As our sample is not identical, but rather extracted randomly, the test will compare the "mean ranks" of the different geographical regions. In the case of the samples being identical, medians would have been compared, something that is important to acknowledge when interpreting the results (NIST, 2015) (Vargha & Delaney, 1998). Kruskal (1952), in Vargha & Delaney, 1998, defines the null hypothesis as "*there is no difference among samples*", and that they come from the same population. The alternative hypothesis states that at least one of the samples tend to yield larger observations than at least one of the other populations (NIST, 2015).

The test statistic is:

$$H = \frac{12}{n(n+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(n+1) \tag{24}$$

Source: (NIST, 2015)

n_i = samples sizes for each of the group of data

R_i = the sum of the ranks for group i

3.10.4 Parametric vs. Non-Parametric tests

The distinction between the two groups of tests is primarily based on the level of measurement represented by the data that are being examined. A general perception exists among researchers stating that as long as there is no reason to believe that the assumptions of the parametric models are violated, the data should be evaluated with an appropriate parametric test. Nevertheless, if one or more of the parametric assumption is violated, some believe it to be prudent to transform the data into a compatible format with the appropriate non-parametric test (Sheskin, 2003).

The primary goal of comparing the effects between parametric and non-parametric statistical tests is to reveal the method that provides the most robust results. While some researchers find the non-parametric result to yield more accurate results (Cowan, 1992) (Dutta, 2014), others state that non-parametric tests should not be used as stand-alone tests (MacKinley, 1997). Research papers involving event studies of merger announcements mainly apply parametric tests, with the student's t-test being the preferred statistical test. On these grounds, we chose to follow the same strategy and use the non-parametric test as a robustness check. This enables a better discussion as we can compare our results directly to previous findings.

4.0 Sample and Data

The databases available for collecting deal data on M&A transactions, market index data, stock data and fundamental accounting data for each acquirer are numerous. The following section therefore aims to describe how and why we ended up with our final sample of deals, as well as to provide a detailed description of the explanatory variables applied in the multiple regression analysis.

4.1 Data Selection

Our data selection is based on the purpose of this paper, past literature, discussions with our supervisor, and insights we gained from interviews with Einar Bjering. There are several different databases available, e.g., *Zephyr, Merger Market, Thomsen One,* etc. with extensive information on M&A deals. However, given expensive subscription fees, we are limited to those provided by CBS. After explaining the purpose of this thesis to one of the experts at the CBS Library, we were recommended to use the Zephyr database. As a result, only deals that are included in Zephyr are a part of our sample. To generate the most accurate sample possible, we used specific criteria to eradicate irrelevant observations. Specifically, we followed a two-step process where the first one provided us with an initial pool of data, whereas the second one aimed at limiting our dataset to exclusively suitable deals.

4.1.1 Selection criteria for initial data

The following criteria were used to delineate our initial pool of data in Zephyr:

1. Industry classification of the acquirer	**2. Listed acquirer**
3. Time period	**4. Deal type**
5. Current deal status	**6. Geographic region**
7. Deal value	

Table 4.01: Selection criteria for initial data

4.1.1.1 Industry classification of the acquirer

To end up with the most relevant pool of companies, we used the Standard Industrial Classification provided by the Office of National Statistics (UK SIC 2007). We only included acquirers with a primary SIC code in division 61, consisting of the following four groups: wired telecommunications activities, wireless telecommunications activities, satellite telecommunications activities, and other telecommunications activities (Office for National Statistics, 2007). We could have used division 48 in the US SIC provided by the United States Department of Justice. However, this division includes seven groups and therefore a broader and less specific pool of companies (United States Department of Labor, u.d.). By using the US SIC codes we

would have ended up with a bigger pool of data, but less directly connected to telecommunication, which could have biased our results.

4.1.1.2 Listed acquirer

The idea behind an event study is to investigate the market's reaction to an event, in this case, an M&A announcement, by using market returns (Wharton Research Data Services, u.d.). Given this, the availability of stock prices for our chosen firms is crucial. By including solely listed acquirers, we make sure that we have the needed stock data, in addition to financial data and company announcements. All this combined allow us to create a more comprehensive analysis.

4.1.1.3 Time period

We have limited our dataset to only include deals that were announced between 01.01.1998 and 31.12.2016. Over this time span, the telecom industry underwent major changes and a high number of M&A transactions, as previously outlined. By looking at such a long period of time, we are able to catch the effects of merger waves and other movements in the industry, as well as shifts in the world economy as a whole. Another argument for our selected time period is our use of the Zephyr database, as the Zephyr database has coverage of deals dating back to 1997 (Weimar-Rasmussen, Lauritsen, Kjærsgaard-Andersen, & Svarrer, 2011). We will make the assumption that the accuracy of information increases over time and that Zephyr most likely lacks some deals around the time of launch. Therefore, we exclude the first year and set the start date to 01.01.1998. Based on the same argument, we end our sample on 31.12.2016 to exclude the possibility of Zephyr lacking information on relevant deals in 2017. This is both due to the potential of the deals not being completed as well as the time lag in the data being added to the database.

4.1.1.4 Deal type

Zephyr includes many different transactions besides mergers and acquisitions, like management buy-in and buy-outs, Initial Public Offerings (IPOs), share buy-backs, etc. Given that we are solely interested in investigating the effect of transactions that are categorized as either a merger or an acquisition, only these two were selected.

4.1.1.5 Current deal status

To ensure that we have all the required deal data available the current deal status must be defined as *completed*. Zephyr further subcategorizes these into two: *completed-confirmed* and *completed-assumed.* This indicates that in some situations a deal has not been confirmed. However, Zephyr has in this case

collected all the needed information. Therefore, we include both subcategories to include all relevant transactions.

4.1.1.6 Geographic region

All acquirers in our sample must origin from the G10 countries, which consist of Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom and United States. By selecting this group of ten (eleven, as Switzerland joined in 1964), we are able to cover most of the major firms in the telecommunication industry, except for Chinese firms. We could have solely selected countries based on the size of the telecommunication industry. However, given that China is an emerging economy, and the rest of the key countries in the industry have to be categorized as developed markets, we chose to focus on the G10 countries. By including these countries, combined with the previously mentioned delimitation that the acquirer has to be listed, all our companies are listed on one of the largest stock exchanges in the world. Given the listing requirements and the high standards of these exchanges, the price stability of the stocks rise, generating a great basis for an event study (Rieck, 2010).

4.1.1.7 Deal value

All deals included in our sample have a deal value greater than €10 million. By excluding the transactions with the lowest deal value, we ensure that our sample consists of deals that should be large enough to affect the value of the acquirer's stock price. We set the threshold to €10 million as this is commonly used in previous studies (Högholm, 2016) (Chang, 1998) (Datta & Puia, 1995). We could have limited our dataset based on market capitalization instead. However, the Zephyr database made this problematic. In cases where the market capitalization of the firm is missing from the database, Zephyr automatically sets the value to zero. Therefore, limiting our dataset based on market capitalization would exclude a vast number of deals that could have been of interest in our study.

4.1.1.8 Summary

When searching for deals in Zephyr with the restrictions discussed above, we end up with an initial sample of 575 deals, all announced and assumed completed between the 1st of January, 1998 and 31st of December, 2016. The results from the initial search strategy in Zephyr can be found in Table 4.2.

Criteria	Search result
Listed/Unlisted/Delisted companies: Listed acquirer	302,851
Current deal status: Completed	241,269
Time period: on and after 01-01-1998 and up to and including 31-12-2016	226,642
World regions: G10 (Acquirer)	130,385
UK SIC 2007 (primary codes): 61 – Telecommunication (Acquirer)	3,674
Deal type: Acquisition, Merger	1,430
Deal value (mil EUR): min = 10	575
Initial sample	**575**

Table 4.02: Search strategy in Zephyr
Source: Zephyr - Bureau van Dijk (2018)

4.1.2 Selection criteria for final data

To guarantee that the final sample solely consists of relevant deals of interest, we added the following criteria:

1. Acquirer's country must be a part of G10	**2.** The acquirers SIC codes are correct
3. Exclude deals with a minority stake	**4.** Exclude deals with two or more acquirers
5. Exclude deals with two or more targets	**6.** Stock price data must be available on Datastream
7. All financial data must be available on WRDS Compustat	**8.** The data on Zephyr must be conclusive
9. Missing exchange rate	**10.** Insignificant model in R
11. Removal of overlapping deals	

Table 4.03: Selection criteria for the final sample

4.1.2.1 Acquirer's country must be within G10

When sampling our initial deal data, we included a requirement that the acquirer had to be from one of the G10-countries. To secure that this requirement had in fact been kept, we examined the country codes provided by Zephyr and removed deals including acquirers outside the G10 countries. A manual investigation of each deal revealed three cases of acquirers being from outside G10, indicating that Zephyr is not without flaws. For this reason, further checks are necessary, when possible, to make sure that our dataset only contains relevant deals.

4.1.2.2 The acquirers SIC codes are correct

As an extra step to ensure that the dataset provided by Zephyr only includes relevant firms, we cross-referenced the SIC codes with Wharton Research Data Services' (WRDS) Compustat database. This further examination showed that all the SIC codes were consistent, and we did not remove any deals in this step.

4.1.2.3 Exclude deals with a minority stake

By the definition provided earlier in this paper, an acquisition is a takeover where the acquirer ends up with a controlling stake in the target, i.e., acquiring an ownership stake exceeding 50 %. It is true that in some cases an acquirer can control a target even with less than 50% ownership of the target's shares. Rieck (2010) argues that it is hard to determine whether or not an acquisition which results in less than a 50% ownership stake generates a controlling stake, without having in-depth knowledge of the deal and the firms involved. Given our inability to gain this knowledge in the available time frame, we chose to exclusively include deals that resulted in a majority stake, above 50%, for the acquiring firm.

4.1.2.4 Exclude deals with two or more acquirers

Given that the purpose of this paper is to find the wealth effect an M&A announcement has on the acquiring firm, we solely include deals where there is only one acquirer. In deals including more than one acquirer, the different parties share both the risk and the rewards. Considering our estimation model, we can only test the wealth effect of one firm for each deal. Given the complexity that deals of this size have, it is hard to split the deal information accurately between the acquirers without a great deal of insider knowledge. We therefore exclusively include deals with one acquirer.

4.1.2.5 Exclude deals with two or more targets

In some cases, companies announce the acquisitions of more than one target company in the same announcement, or they have bought several companies as parts of the same deal. In these situations, it may be hard to differentiate between how the different targets affect the acquirer. Another issue regarding these circumstances is the nature of the various targets. Seeing that we want to separate deals based on the relation between the acquirer and the target, it becomes a problem if the targets have differing relations with the acquirer. Thus, we exclude all deals with two or more targets.

4.1.2.6 Stock price data must be available on Datastream

In order to perform the steps outlined in the *Methodology* section, daily stock price data for each company is required in both the estimation and event window. This step matches the initial criteria that the acquirer

has to be listed. To collect the needed stock data, we use Thomas Reuters' Datastream. Datastream is extensively used in previous research and contains over 6.1 million time series on financial data (Thomson Reuters, u.d.). Thus, we believe this to be a trustworthy and reliable source. To account for possible stock splits, we used the adjusted stock price. If the required stock data was missing in Datastream, the deal was removed. To increase the validity and reliability of the data from Datastream, we cross-referenced a random sample from our stock data with Yahoo Finance.

4.1.2.7 All financial data must be available on WRDS Compustat

To account for firm-specific factors in the analysis, we need annual financial information on each acquirer. With the aim of consistency in the data, we wanted to gather the financial information from Datastream, as this was the database which we retrieved the stock data. However, Datastream only had the required information on a limited number of the firms in our sample. Therefore, we decided to use WRDS Compustat, well aware of the possibility of information errors this mixing of databases generates. WRDS Compustat is a leading financial research platform with over 250 terabytes of various data. The database has over 50,000 users in more than 30 countries, making it a highly reliable source (Wharton Research Data Services, u.d.). If we were unable to find the required financial data for a given time period, all the deals made by the respective firm in that period were removed.

4.1.2.8 The data on Zephyr must be conclusive

Zephyr can provide a lot of information regarding each merger transaction, for example, company information, deal types, the method of payment, geographic and industry affiliation, etc. We decided on a number of variables we would need for our analysis and removed the deals where information on these variables was lacking.

4.1.2.9 Missing exchange rate

As previously mentioned, we used Datastream to download security data and Compustat to download fundamental financial data. Given our global approach, the output is displayed in various currencies. In some situations, Datastream and Compustat provide different currencies for the same company. Since we are using some variables that mix stock data and financial data (e.g., when calculating Tobin's Q), it is essential that the currency is unanimous. In the cases where the provided data is in different currencies, we have used historical exchange rates from Datastream to transform the security data to match the financial data from Compustat, by matching their ISO currency codes. In two of the events, the security data was presented in

obsolete currencies, and we were unable to obtain the historical exchange rates; hence we had to remove the deals.

4.1.2.10 Insignificant market model in R

As presented in the methodology section, we regressed five indices against each firm's return over the whole sample period to determine which index to use for the various firms. In two cases, none of the indices resulted in a significant model, in which case we removed the deals from our final sample.

4.1.2.11 Removal of overlapping deals

Sorescu, Warren and Ertekin (2017) address the main challenges when conducting an event study. One of these being the topic of overlapping events. It is common when designing an event study on company announcements of some sort that one company has multiple announcements in a short period. If one announcement is located within the estimation window of another, this announcement will affect the accuracy of normal returns. This issue is called the confounding effect. Sorescu et al., (2017) review 42 papers to figure out how previous literature dealt with this problem. They find that 50% of the papers explicitly state that they eliminate the overlapping observations; thus, we decided to do the same Sorescu et al., (2017). A list of the acquiring firms included in the final sample, can be found in Appendix 3.

4.1.2.12 Final sample

Our delimitation above results in the following final sample:

Initial sample	**575**
Acquirer's country must be a part of G10	3
Exclude deals with a minority stake	3
Exclude deals with two or more acquirers	23
Exclude deals with two or more targets	25
Stock price data must be available on Datastream	29
All financial data must be available on WRDS Compustat	25
The data on Zephyr must be conclusive	11
Missing exchange rate	2
Insignificant model in R	2
Removal of overlapping deals	169
Final sample	**283**

Table 4.04: Final sample
Source: Compiled by authors

Out of the 283 remaining deals, 15 were announced on a non-trading day i.e., a day the stock market was closed. Announcements on non-trading days are a problem as we are unable to match the event date to specific firm and market returns. To resolve this problem, we use the solution provided by Peterson (1989) who suggests to simply move the announcement day to the first possible day the market is open.

4.2 Variables

This section starts out with an explanation on how we selected the explanatory variables in this study, before providing a detailed description of each variable and its method of calculation.

4.2.1 Selection process

Our choice of variables is mainly motivated by previous literature. We started out by searching for similar research papers with an aim of determining which variables they included, and which ones they found to have a significant effect on the wealth of the acquirer. By including variables discussed in previous literature, we are able to compare our results directly to other, similar studies. We chose to do a multivariate analysis with several explanatory variables, similar to the approach used by Kirchhoff & Schiereck (2011). They conducted an event study in the Pharmaceutical and Biotechnological industry, and in the following we will check whether we can find similar effects in the telecommunication industry. We discussed possible variables with Martin Linnemann Larsen and Einar Bjering to gain some insight from experts that have been directly involved in numerous M&A deals.

As mentioned, we are going to use OLS estimation to carry out the analysis. Stock and Watson (2015) present four least square assumptions related to the multiple regression model. The fourth assumption refers to the variables and covers a case called perfect multicollinearity. Stock and Watson define perfect multicollinearity as a situation where "*one of the regressors is a perfect linear function of the other regressors"* (Stock & Watson, 2015). The assumption is therefore that the regressors, also referred to as variables, are not perfectly multicollinear. In cases where one of the regressors is very highly, but not perfectly correlated with the other regressors, the situation is referred to as *imperfect multicollinearity*. It is still possible to estimate the regression in the presence of imperfect multicollinearity, but it could result in inaccurate estimates of one or more of the regression coefficients (Stock & Watson, 2015).

To avoid this, we tested for multicollinearity by assessing the correlation coefficients for all our chosen variables. The output from the correlation matrix can be found in Appendix 4. There is no general rule to judge if a correlation is too high. We used a threshold of 0.8 for our sample, as applied by Hobdari (2011). In

situations where the stepAIC chose to include two variables that had a correlation coefficient greater than 0.8, we ran the regression with both variables together as well as separate and decided to add the variable that showed the highest significance.

4.2.2 Dependent variable

After reviewing previous literature, we decided to use CAR as our dependent variable. CAR enables us to draw overall inferences for the event of interest and to accommodate a multi-period event window. In addition, CAR is frequently applied in previous literature. By selecting the variable most suited to our case, as well as a variable commonly used in similar studies, we can compare our findings to past findings. We are going to examine the effect on CAR in three different event windows. Including more than one event window enables us to investigate potential effects surrounding the announcement date. Hence, we aim at controlling for both information leakages prior to the event as well as post-event information delay potentially caused by disseminated information.

4.2.3 Independent variables

We have decided to split the independent variables into three separate groups: firm-specific, deal-specific and external control variables. As the names suggest, the firm-specific variables are related to the acquiring firm's attributes, while the deal-specific variables are tied to characteristics connected to the deal. The external control variables are included to account for various market effects. Each subsection will provide a table with an overview of the selected variables.

4.2.3.1 Firm-specific variables

Our regression analysis contains the eleven firm-specific variables shown in Table 4.5. We have included several key financial ratios to assess different aspects of the financial situation of the various firms. It is normal to divide financial ratios into four separate groups: profitability, efficiency, solidity and liquidity ratios. We have emphasized profitability ratios because of its importance in the telecommunication industry (Karlsson, Back, Vanharanta, & Visa, 2001).

Category	Determinants	Calculation
Cost Efficiency (Kirchhoff & Schiereck, 2011)	Operational costs over time	$\frac{Operational\ Cost_{t-1}}{Operational\ Cost_{t-2}}$
Enterprise Value (Compiled by authors)	Absolute size	$\ln(Enterprise\ Value_{t-1})$
Equity Ratio (Kirchhoff & Schiereck, 2011)	Ratio of equity to total assets	$\frac{Book\ value\ of\ equity_{t-1}}{Book\ value\ of\ total\ assets_{t-1}}$
Liquidity (Kirchhoff & Schiereck, 2011)	Ratio of cash flow to sales	$\frac{FCF_{t-1}}{Sales_{t-1}}$
Merger Experience (Kirchhoff & Schiereck, 2011)	Deals each year for the acquirer and the industry	$\frac{Acquirer\ number\ of\ deals\ in\ year_t}{Industry\ number\ of\ deals\ in\ year_t}$
ROE Trend (Kirchhoff & Schiereck, 2011)	Return on equity over time	$\frac{ROE_{t-1}}{ROE_{t-2}}$
ROA Trend (Complied by authors)	Return on assets over time	$\frac{ROA_{t-1}}{ROA_{t-2}}$
Sales Ratio (Kirchhoff & Schiereck, 2011)	Ratio of sales to total assets	$\frac{Sales\ Revenues_{t-1}}{Book\ value\ of\ total\ assets_{t-1}}$
Sales Trend (Kirchhoff & Schiereck, 2011)	Sales over time	$\frac{Revenue_{t-1}}{Revenue_{t-2}}$
Growth in Assets (Kirchhoff & Schiereck, 2011)	Assets over time	$\frac{Total\ assets_{t-1}}{Total\ assets_{t-2}}$
Tobin's Q (Complied by authors)	Ratio of market value to book value of assets	$\frac{Total\ market\ value\ of\ acquirer_{t-1}}{Book\ value\ of\ total\ assets_{t-1}}$

Table 4.05: Overview of the firm-specific variables included in this paper

4.2.3.1.1 Cost efficiency

We define *Cost Efficiency* as *operational costs* over time. As discussed previously, cost synergies are a common and important motive behind mergers in the Telecommunication industry. When Kirchhoff & Schiereck (2011) analyzed the pharmaceutical and biotechnological industry they found cost efficiency to be statistically insignificant for the abnormal returns of the acquirer. However, given the importance of this motive in the telecommunication industry, we view cost efficiency to be an interesting factor to examine in our analysis.

4.2.3.1.2 Enterprise value

Enterprise Value is an important factor to consider when examining announcement effects on M&A as it can explain differences in abnormal returns for small and large firms. Moeller et al. (2004) find differences in abnormal returns of acquirers depending on firm size. Their results indicate, on average, a negative announcement effect for large firms, while smaller firms experience positive effects. These findings are supported by Gorton, Kahl and Rosen (2009) who find decreasing profitability for increase in firm size. There are at least two theories that can explain this. Gorton et al. (2009) argue that large firms tend to overpay when participating in M&A, while smaller firms do not, and therefore experience positive abnormal returns. Higgins and Rodriguez (2006) present another possible explanation for the different results depending on firm size by suggesting that smaller acquirers have a greater possibility to accomplish economies of scale. We use the logarithm of an entity's enterprise value as a measure of firm size, to handle the potential situation of a non-linear relationship between the independent variable, *Enterprise Value,* and dependent variable, *Abnormal Return* (Benoit, 2011). The variable is calculated using the following formula:

$$\ln(Enterprise\ value) = \ln(Market\ Value\ of\ Equity + Debt - Cash) \quad (25)$$

(Berk & DeMarzo, 2013)

4.2.3.1.3 Equity ratio

The *Equity Ratio* is a solidity ratio and is defined as the ratio of the book value of equity to the book value of total assets. The ratio serves as a good indicator of the financial strength of a company (Kirchhoff & Schiereck, 2011). According to their study, a higher equity ratio positively affects abnormal returns due to its illustrative power when evaluating investors willingness to finance firms' assets.

4.2.3.1.4 Liquidity

We have chosen to use cash-flow-to-sales ratio as an indicator of *Liquidity*. *Liquidity* is an important financial factor to consider when assessing an event's impact on abnormal returns. Kirchhoff & Schiereck (2011) found

that firms with strong liquidity outperform firms with weaker liquidity, showing that the acquirer's liquidity has a positive and statistically significant impact on abnormal returns.

4.2.3.1.5 Merger Experience

As previously mentioned, synergies are a common motive for mergers and acquisitions in the telecommunication industry. After an acquisition, the two firms in question need to be combined into one single unit. To succeed in generating the wanted synergy effects, the merging procedure is critical. This is a complicated process, and we would like to investigate whether the success of this post-integration is correlated with *Merger Experience*. Previous literature including this variable has found contradicting results, with Higgins and Rodreiguez (2006) finding a negative effect, and Fuller, Netter and Stegemoller (2002) finding a positive effect on abnormal returns.

4.2.3.1.6 ROE Trend

Return on equity (ROE) serves as a measure on what return past investments of a firm has generated. If a firm has a high ROE, it demonstrates a firm's ability to find profitable investment opportunities (Berk & DeMarzo, 2013). We have used the yearly percentage increase in ROE as a measure of profitability in our analysis. This variable expresses possible synergies the merger can generate (Kirchhoff & Schiereck, 2011).

$$Return\ on\ Equity\ (ROE) = \frac{Net\ Income}{Book\ Value\ of\ Equity} \tag{26}$$

(Berk & DeMarzo, 2013)

4.2.3.1.7 ROA Trend

Given the importance of profitability measures in the telecommunication industry (Karlsson et al., 2001), we have chosen to include *ROA Trend* as an additional measure. We define *ROA Trend* as the yearly percentage increase in ROA. By using both ROE and ROA as performance measures, we improve the accuracy of our results, since ROE and ROA are sensitive to different factors of a firm's financials (Berk & DeMarzo, 2013). The assets in the denominator have been funded by both equity and debt. Berk and DeMarzo (2013) use net income in the numerator and subtract interest expense. By doing so, they are able to look at the operating returns before the cost of debt. However, by adding back the interest expense, they negate the impact of higher debt. Since a greater amount of debt can significantly increase the solvency risk of a company, we would like to include the cost of borrowing, and choose to apply the formula used by Petersen and Schoeman (2008):

$$Return\ on\ Assets\ (ROA) = \frac{Net\ Profit\ After\ Taxes}{Book\ Value\ of\ Assets} \quad (27)$$

(Petersen & Schoeman, 2008)

4.2.3.1.8 Sales Ratio

Given that strong financial performance can facilitate merger transactions, *Sales Ratio* is another important factor to consider. We define *Sales Ratio* as the ratio of sales to total assets, providing information about the sales power of a given company (Kirchhoff & Schiereck, 2011). Kirchhoff and Schiereck's (2011) results reveal a positive and significant relationship between sales performance and abnormal returns.

4.2.3.1.9 Sales trend

In addition to the *Sales Ratio*, we include *Sales Trend* as an indicator of financial performance. *Sales Trend* is defined as the yearly change in revenues and illustrates whether a firm is able to increase their revenues, or if it has a negative trend. Reddy, Qamar & Yahanpath (2017) found sales growth to affect abnormal returns positively, concluding that firms that are able to grow their revenues are rewarded with higher returns.

4.2.3.1.9.1 Growth in Assets

Similar to the variable *Sales Trend*, we incorporate a variable for *Growth in Assets* defined as the annual change in assets. *Growth in Assets* is a relevant factor to consider when examining stock returns, emphasized by several previous studies that found a negative impact of asset growth on abnormal returns (Fu F. , 2011) (Cooper, Gulen, & Schill, 2008).

4.2.3.1.10 Tobin's Q

Tobin's Q is defined as the ratio of market value to book value of total assets. Viewed from an investor's perspective, *Tobin's Q* can symbolize the value of a given company (Kasmawati, 2016). By including *Tobin's Q*, we will simultaneously control for much of the same effect as for the P/B (Price-to-book), multiple. Previous literature has found that Tobin's Q indicates profitable opportunities to M&A (Chappell Jr. & Cheng, 1984) (Gehringer, 2015). Given these findings, we see that Tobin's Q is an important variable to consider when analyzing abnormal returns in the telecommunication industry.

4.2.3.2 Deal-specific variables

Our regression analysis contains four deal-specific variables as presented in the below Table 4.6.

Category	Determinants	Calculation
Related/Unrelated (Kirchhoff & Schiereck, 2011)	2 digits SIC codes	0: Related 1: Unrelated
Method of Payment (Kirchhoff & Schiereck, 2011)	The primary method of payment provided by Zephyr	0: Cash 1: Shares 3: Other
Domestic/Cross-border (Kirchhoff & Schiereck, 2011)	Location of acquirer's headquarter vs. location of target's headquarter	0: Domestic 1: Cross-border
Prior Ownership (Compiled by autors)	Did the acquirer own parts of the target prior to the deal?	0: No 1: Yes

Table 4.06: Overview of the deal-specific variables

4.2.3.2.1 Related/Unrelated

To identify whether a merger is related or unrelated, we first compare the primary US SIC Codes of the acquirer and the target on a two-digit level. When establishing our initial sample, we decided to use the UK SIC codes as these offer a group specified as *Telecommunication*. The US SIC codes have a broader classification and include telecom companies in a bigger group called *Communication*. Therefore, as argued earlier, we used UK SIC to ensure the sole inclusion of relevant companies. However, when categorizing whether two companies are related or unrelated in terms of operations, we have used the US SIC codes. This is because we believe that mergers with additional companies outside those included in the *Telecommunication* group could be classified as related. We therefore choose to employ the US SIC codes for this purpose.

The classification on a two-digit level is a rather simple classification, but previous studies have found it highly corresponding with more advanced methods, and for this reason, we find it adequate (Montgomery, 1982). All primary SIC codes of the acquirers are under the major group 48: *Communications*. Whenever the first two digits of the primary SIC Code of the target also are 48, we define the deals as related, and if the first two digits are something else, the deal is categorized as unrelated. As an additional check, we have researched each deal to check whether the two-digit categorization makes sense. Wilcox et al. (2001) found

that related mergers outperform unrelated ones, showing the possibility of increased synergy effects when merging with companies within their own sector.

4.2.3.2.2 Method of Payment

The impact of *Method of Payment* on abnormal returns has been widely researched over the years. Several studies have found that deals where shares are the primary source of payment, experience significantly negative abnormal returns. If on the other hand, cash is the primary source of payment, the effect on abnormal returns are zero or marginally positive (Asquith, Bruner, & Mullins Jr., 1987) (Huang & Walkling, 1989) (Yook, 2003). The Zephyr database provides us with information about the primary source of payment in each deal. We particularly want to check whether there are differences in abnormal returns if the payment is made with either cash or shares, or the last category containing all other payment alternatives, classified as *Other.* Cash is defined as the base case with the dummy variable zero, shares takes the value one, while the deals with other primary methods of payment takes the value of two.

4.2.3.2.3 Domestic/Cross-border

Given the globalization of the telecommunication industry over the last 20 years, there have been a number of cross-border transactions in addition to the more traditional domestic deals. To account for the possible differences in abnormal returns in a domestic versus an international deal, we include a dummy variable to represent the nature of the transaction. Aybar & Ficici (2009) analyzed the wealth effects of 433 M&A and found that cross-border M&A had a negative impact on the acquiring firm in more than 50% of the deals.

4.2.3.2.4 Prior Ownership

All the mergers in our sample are transactions which resulted in a controlling stake, i.e., majority ownership of the target. However, in a number of the transactions, the acquirer had an initial ownership stake in the target. It is natural to believe that acquirers with an initial stake in a target have superior knowledge about the target, compared to acquirers with no *Prior Ownership*. This will, in turn, provide the acquirer a better assessment of the possibility of a successful merger. Besides, several researchers have found evidence that having an initial stake in the target prior to the merger generated significantly positive abnormal returns at the announcement time (Frame & Lastrapes, 1998) (Yang, 2014).

4.2.3.3 External Control Variables

In addition to the firm-specific and deal-specific variables presented above, we include three external control variables to account for various market effects. The variables *GDP* and *Interest rate* are added to capture the

impact of economic trends in our geographical areas, while the merger wave position variable is included to catch any industry-specific merger trends.

Category	Determinants	Calculation
M&A Wave Position (Complied by authors)	Total number of deals in the industry and the respective acquirers each year	$\frac{Number\ of\ deals\ in\ industry_t}{Number\ of\ deals\ in\ industry_{t-1}}$
GDP (Complied by authors)	Yearly change in the gross domestic product of each country of interest	$\frac{\%\ change\ GDP_t}{\%\ change\ GDP_{t-1}}$
Interest Rate (Complied by authors)	The interest level of the country in question	

Table 4.07: Overview of the external control variables

4.2.3.3.1 M&A Wave Position

A previously mentioned, the telecommunication industry experiences merger waves. These waves are driven by industry shocks, such as technology, regulatory and economic shocks. Given the significant impact a merger wave can have on an industry, we view this as an important factor to consider. Besides, previous empirical findings are relatively unanimous about being at the peak of a merger wave have negative impact on abnormal return, explained by increased competitions and premiums during periods with high merger activity (Duchin & Schmidt, 2013) (Ismail, Abdou, & Annis, 2011).

4.2.3.3.2 GDP

Previous studies have found it hard to measure the effect of macroeconomic factors on abnormal returns (Flannery & Protopapadakis, 2002). To account for the possible effects, macroeconomic factors can have on the financial markets we include three such variables in our analysis: *GDP*, *Interest rate* and the previously mentioned *M&A Wave Position*. We have used the yearly GDP rate of each of the countries in the G10 provided by OECD, which are seasonally adjusted and calculated as the percentage change of real GDP from the previous year (Organisation for Economic Co-operation and Development, 2018). As we can see from *Figure 4.1*, the GDP development in the G10 countries is highly correlated. They mostly exhibit a positive growth with the natural exception in the period following the financial crisis in 2008.

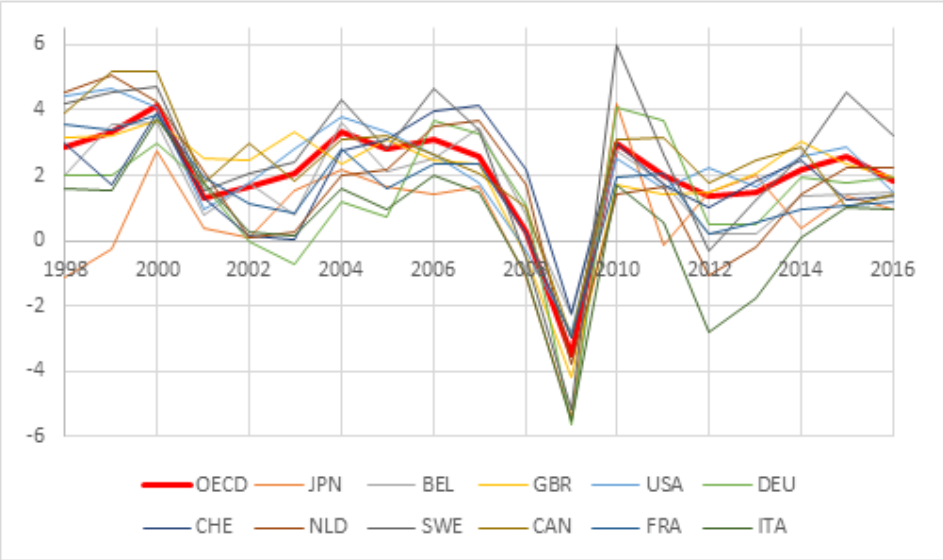

Figure 4.01: Development of the GDP in the G10 countries from 1998-2016
Source: (Organisation for Economic Co-operation and Development, 2018)

4.2.3.3.3 Interest Rate

As mentioned above, the third macroeconomic factor we include is *Interest Rate*. The idea behind this is that a low interest rate generates a lower cost of capital. We would like to investigate if this lower cost of capital causes higher abnormal returns as the cost of acquiring would be relatively cheaper compared to when the interest rate is high. We have used the long-term interest rates provided by OECD as the measure. They calculate the interest rate based on government bonds maturing in ten years (Organisation for Economic Co-operation and Development, 2018).

5.0 Hypotheses

Since we are going to test our models across different samples representing mergers in different geographical regions, we have constructed different hypotheses to establish a structure for the *Results* and *Discussion* in Sections 6 and 7, respectively. We have divided our hypotheses into two main groups: one testing the significance of the abnormal returns, and the other examining the independent variables on the abnormal returns in our multiple regression analysis. Furthermore, we split our sample into different regions and make the same interpretation over the different event windows of interest.

5.1 Testing AR and CAR

Our first hypothesis concerns the investigation of the effects on abnormal returns and cumulative abnormal returns within the different event windows.

Hypothesis 1: *The AR and CAR are not significantly different from zero in the three symmetric event windows [-1, 1], [-5,5] and [-10,10]*

Next, we divide our total sample into three different subsets, representing the geographical regions of interest. This will help us differentiate between the effects of merger announcements across regions and make it easier to look for similarities and differences.

Hypothesis 2: *The significance or signs of AR and CAR is not dependent on geographical location*

Following, we present a table of how we imagine the total sample, as well as the different samples' CAR, will react to a merger announcement. Our hypotheses are based on previous literature on the same topic as well as our knowledge. As the majority of the research papers on the area have concluded on mergers being either significantly or insignificantly unprofitable for the bidding firm, we hypothesize that these effects will show in our sample as well. As country-specific studies are rare, we have no reason to believe that we will find differences across regions. An overview of our expectations to the reaction in abnormal returns would be found in Table 5.1.

	CAR[-1,1]	CAR[-5,5]	CAR[-10,10]
Total Sample	Negative	Negative	Negative
North America	Negative	Negative	Negative
Europe	Negative	Negative	Negative
Japan	Negative	Negative	Negative

Table 5.01: Initial expectations to the effect on abnormal returns
Source: Compiled by authors

5.2 Testing the Multiple Regression

When looking at the results from the multiple regression, we want to determine which, if any, factors that have a significant impact on abnormal returns. In line with our setup in Section 4, *Sample and Data*, we have separate hypotheses for the firm-specific and deal-specific variables:

Hypothesis 3: The firm-specific explanatory variables have no significant effect on the abnormal returns resulting from a merger announcement.

Hypothesis 4: The deal-specific explanatory variables have no significant effect on the abnormal returns resulting from a merger announcement.

Since we are interested in finding variables with a significant impact on abnormal returns, we aim to reject both hypotheses. Furthermore, we are interested in whether there are any differences in which factors that have a significant impact in the different geographic regions. Additionally, given that one or more variables occur in several regions, we want to examine if the variables affect abnormal returns in the same direction and if they differ in magnitude. We therefore aim to reject the following hypothesis:

Hypothesis 5: There is no difference in factors across geographical locations in terms of significance and sign of the regression coefficients.

Based on previous literature, we have made initial predictions on the direction of impact on each of our independent variables. In the discussion in Section 7, we want to investigate and discuss whether our results are in line with the predictions made before the analysis. Table 5.2 below shows our theories.

	Effect		Effect
Liquidity	+	M&A experience	+
ROE-trend	+	Enterprise value	-
ROA-trend	+	Related/Unrelated	-
Sales ratio	+	Payment1	-
Sales trend	+	Prior ownership	+
Equity ratio	+	Domestic/Cross-border	-
Tobin's Q	+	M&A wave	-
Cost efficiency	+	GDP	+
Growth in Assets	-	Interest rate	-

Table 5.02: Initial expectations of the effect of the independent variable on abnormal returns
Source: Compiled by authors

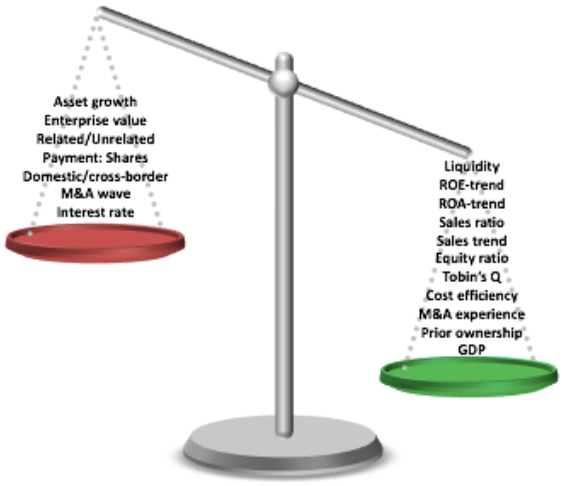

Figure 5.01: Illustration of initial expectations for the regression
(separating negative (red) and positive (green) variables)

As seen from Table 5.2 as well as Figure 5.1, we believe that eleven of our selected variables will have a positive effect, while that the remaining seven will have a negative impact on abnormal returns. Based on the importance of profitability measures emphasized by Karlsson et al. (2001) we have included several variables that indicate how profitable a company is. We believe that higher profitability, liquidity and solidity ratios should result in higher abnormal returns. As a result, we believe that *Liquidity*, *ROE*- and *ROA-Trend*, *Sales Ratio*, *Equity Ratio*, *Tobin's Q*, *Cost Efficiency* and *Sales Trend* should all have a positive effect. Furthermore, as previously mentioned, based on the complexity of combining two different entities, we believe that greater *M&A Experience* should generate higher returns.

In addition to the aforementioned firm-specific variables, we expect one deal-specific and one control variable to have a positive impact. *Prior Ownership* in the target firm should give the acquirer more insight and opportunity to assess whether a potential merger could be profitable. Furthermore, an initial stake could also smoothen the integration process of the acquired firm. The control variable expected to have a positive effect is *GDP*. A higher GDP indicates a higher economic performance in the region as a whole, which could affect the stock returns of the acquirer positively.

Besides the variables mentioned, we believe the remaining seven variables to have a negative impact. Two of these variables are firm-specific, three are deal-specific, and the remaining two are control variables. In line with the findings by Fu (2011) and Cooper et al. (2011), we believe that *Growth in Assets* has a negative impact on abnormal returns. Their findings are consistent with other papers examining the same effect. The overall consensus is that asset growth is strongly linked to lower expected future returns (Berk, Green, & Naik, 1999) (Gomes, Kogan, & Zhang, 2003) (Carlson, Fisher, & Giammarino, 2004) (Anderson & Garcia-Feijoo, 2006) (Fama & French, 2006). The other firm-specific variable that we believe will have a negative impact is *Enterprise Value*. Previous research suggests that small firms earn higher returns in M&A deals than larger firms, implying a negative relation between firm size and abnormal returns (Moeller et al., 2004) (Gorton et al., 2009) (Rieck, 2002).

We believe that three of our four deal-specific variables will have a negative effect in our analysis. The first is the variable that indicates whether a merger is between *Related/Unrelated* firms. Aligned with studies by Wilcox et al. (2001), Georgen & Renneboog (2004) and Seth (1990) we expect to find a negative coefficient, indicating that unrelated M&A results in lower abnormal returns than related ones. The next deal-specific variable presumed to be negative is *Payment1,* which represents deals where shares were the primary source of payment. Previous studies examining the effect source on payment has on abnormal returns find that

deals paid in cash have statistically significant greater abnormal returns compared to those paid with shares (Asquith et al., 1987) (Huang & Walkling, 1989) (Georgen & Renneboog, 2004) (Yook, 2003) (Andrade et al., 2001). We expect to find a similar connection in our study. The last deal-specific variable is *Domestic/Cross-border*. As a result of the cross-cultural differences between companies in different countries, we believe that the unification of two firms from different geographic regions will generate lower abnormal returns than those within the same country. Thus, we expect the coefficient on the *Domestic/Cross-border* variable to be negative.

Finally, we expect two of the control variables to negatively impact abnormal returns, namely *M&A Wave Position* and *Interest Rate*. If a merger is positioned in an M&A wave, there are a high number of deals happening at the same time. This makes it harder for firms to achieve their goals given higher competition, and higher premiums on target firms. Regarding *Interest Rate*, we believe that this can negatively affect abnormal returns through higher cost of capital. An increased cost of capital would make mergers financed with debt more expensive, which could have a negative impact on how the market reacts to the announcement.

6.0 Results

This section of the thesis will be used to present and elaborate on the results of our analysis. The function of this paper is to identify movements in abnormal returns, and whether firm-specific and deal-specific variables affect these movements across different regions. To make the analysis easier to follow we are presenting the results in the same order as our hypotheses. The results will be further discussed and compared to earlier findings in Section 7, *Discussion*.

First, we will interpret the estimates of alpha and beta obtained from the market model. The alpha and beta for each deal can be found in Appendix 5. Second, we will present the results of the parametric and non-parametric tests on AR and CAR (***Hypothesis 1***) before we identify any potential differences in M&A announcement reactions between our three different geographical regions (***Hypothesis 2***). Third, we will present our multiple regression model, starting off with the base case including the total sample (***Hypothesis 3 and 4***). Lastly, we will subset the total sample into our three regions, Europe, North America and Japan to be able to identify whether some regions are driving the results of the total sample (***Hypothesis 5***).

6.1 Market Model Estimates

Before running the market model regressions, we had to decide which market index to apply for each company. This was done by running the five different regressions as discussed in Section 3, *Methodology,* and identifying the best-fit market index for each individual deal. As mentioned, an example of the regression output can be found in Appendix 2. Furthermore, when running the market model, we created a loop in the statistical software *R Studio*. By simply changing the start and stop date for the estimation window, we were able to estimate the market model's alpha and beta for several event windows. The constructed code can be found in Appendix 6. All market model regressions are calculated using a 130-day estimation window. The average estimates from our market model regressions are found in Table 6.1.

Summary Statistics						
	CAR[-1,1]		**CAR[-5,5]**		**CAR[-10,10]**	
	Alpha	**Beta**	**Alpha**	**Beta**	**Alpha**	**Beta**
Mean	0.0002	0.7833	0.0002	0.7816	0.0002	0.7845
Standard Deviation	0.0016	0.4141	0.0016	0.4117	0.0015	0.4073
Minimum	-0.0059	-0.492	-0.0068	-0.4953	-0.0062	-0.4186
Maximum	0.0068	2.7217	0.0065	2.6346	0.0056	2.4782
Number of Observations	283	283	283	283	283	283

Table 6.1: Summary statistics on the Market Model
Source: Complied by R studio

From Table 6.1, it can be seen that the alpha is very close to zero, while beta lies close to one for all event windows. A conventional t-test reveals that the alpha is not significantly different from zero, and that beta is not significantly different from one, confirming their natural conditions (Munk, 2015 p. 312). This could also be seen from the minimum and maximum values, that for alpha and beta, contains the values zero and one, respectively. The range of the minimum and maximum of the alpha is reasonable, while for the beta, the range is broader.

According to Munk (2017), the beta values measure how sensitive a security is to the return on the market portfolio. The fact that the average beta is smaller than one for all event windows, theoretically indicates that the telecommunication market is less volatile than the market. Hence, a beta of 0.78 implies that the sample average is 22% less volatile than the market (Munk, 2017). We have used the 130 days estimation window instead of the just as common 250-day estimation window (MacKinley, 1997) (Bijoy & Sehgal, 2015). Even though it could be argued that a longer estimation window will provide more accurate results, it may also be a poor representation of the future returns. Additionally, a longer estimation window would generate a higher number of confounding events, further decreasing our sample size. For these reasons, we believe that applying the short-term beta will provide an estimate closer to the individual stocks' level of systematic risk.

6.2 Hypotheses 1 and 2: Testing the significance of AR and CAR

As previously discussed, the analysis of the effects on AR and CAR are divided into two separate sections. First, the total sample is reviewed, discussing *Hypothesis 1*. Following the initial results, we will present the results from *Hypothesis 2*, potentially unveiling similarities and differences across regions, enabling us to explain the aggregated effect of the total sample.

6.2.1 Hypothesis 1: Testing the significance of AR and CAR for the total sample

Hypothesis 1: *The AR and CAR are not significantly different from zero in the symmetric event windows, [-1, 1],[-5,5] and [-10,10]*

First, the parametric t-test of the cumulative abnormal returns shows the same patterns through all three event windows. The reaction in cumulative abnormal returns is significantly negative at a 1% level in the event windows [-1, 1] and [-5, 5], and at a 10% significance level for the event window [-10, 10]. Hence, when

including the total sample in the analysis, we find that announcements of mergers have a significantly negative impact on the stock price.

Event window	CAR	T-test: CAR = 0
CAR[-1,1]	-0.39%	-12.2377***
CAR[-5,5]	-0.23%	-3.5667***
CAR[-10,10]	-0.19%	-1.6768*
*p < 0.1 ; **p < 0.05 ; ***p < 0.01		

Table 6.2: CAR reactions and parametric results on CAR for the total sample
Source: Complied by authors

Second, from looking at the graphs in Figure 6.1, it can be seen that abnormal returns in the two largest event windows increase prior to the announcement, while all event windows show a drop in AR on the day of the announcement (Day 0), which is significant at a 95% confidence level. The reduction in AR moves CAR down to a new level before it continues to fluctuate.

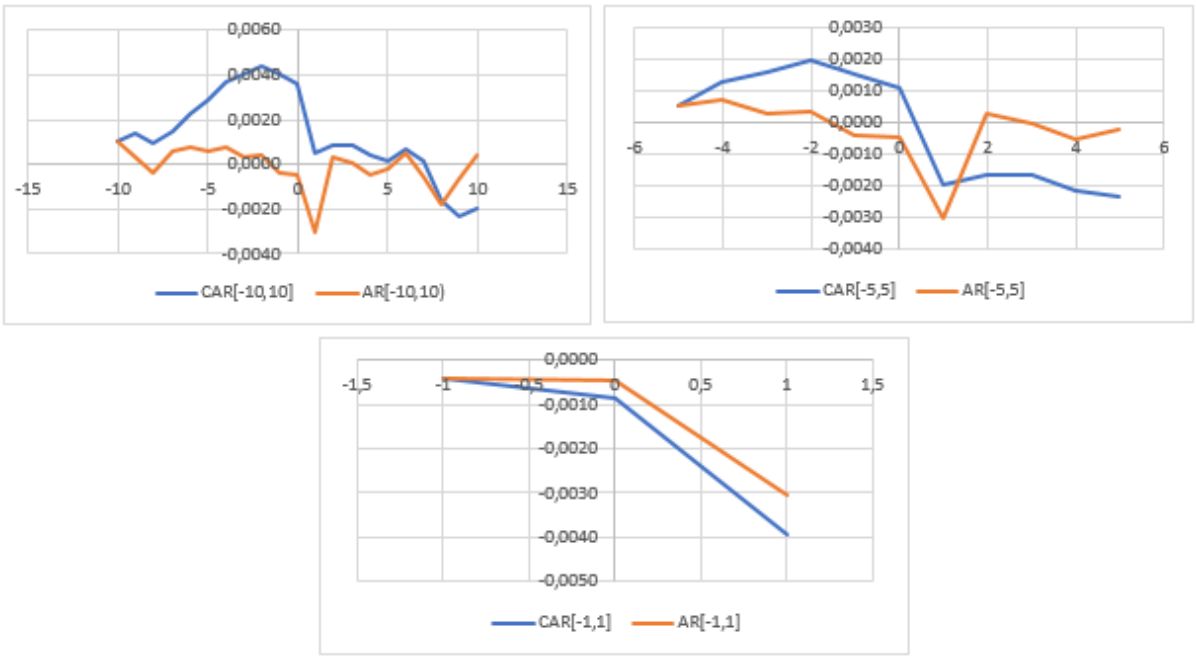

Figure 6.1: Graphical illustration of the AR and CAR development for total sample
Source: Complied by authors

In Appendix 7, you will find all average figures on AR and CAR for the total sample. The results portrayed in Appendix 7 show the interesting observation that the abnormal returns experience a significant decrease at the day following the announcement day, something that could be a result of delayed information flow regarding the merger announcement towards the market. From Appendix 7, there is also reported test-

statistics form the non-parametric sign test, showing a similar pattern in terms of increasing/decreasing returns as well as the pattern of significant abnormal returns. Hence, this shows further validation of the results obtained from the parametric t-test. Regardless of the movements within the three event windows, the main finding in the total sample implies announcement of mergers to produce significant adverse returns.

The overall findings in the total sample show the same consensus in all event windows, where the null hypothesis of AR and CAR not being significantly different from zero is rejected. Following, we will use the sample datasets of the different regions to examine whether there are differences in stock price reactions across geographical areas.

6.2.2 Hypothesis 2: Testing the significance of AR and CAR for each region

By dividing our total sample into three different region-specific samples, we hope to reveal similarities and differences in the stock price reaction across regions around the announcement date. Hence, we want to answer our second hypothesis:

Hypothesis 2: *The significance or signs of AR and CAR is not dependent on geographical location*

6.2.2.1 North America

When running the parametric test on CAR for the North American subset, we find similar patterns as those found for the total dataset. The reaction on CAR is significantly negative at the 95% confidence level for all event windows. Thus, isolating the effect of North American deals will not change the interpretation of CAR. When announcing a merger in the US or Canada, the stock prices of the companies will, on average, have a significantly negative impact.

Event window	CAR	T-test: CAR = 0
CAR[-1,1]	-0.88%	-7.9269***
CAR[-5,5]	-0.81%	-3.6493***
CAR[-10,10]	-1.62%	-4.5699***
*p < 0.1 ; **p < 0.05 ; ***p < 0.01		

Table 6.3: CAR reactions and parametric results on CAR for North America
Source: Complied by authors

Turning to the effects on AR, it can be observed from the graphs in Figure 6.2 that the abnormal returns start dropping prior to the actual event, showing possible signs of information leakage towards the market. Besides, by analyzing the day-by-day output from Appendix 8, we can observe a similar pattern as for the total sample, where we see a significant decrease in AR on the day after the announcement. The fact that the results are consistent with the total sample can be an indication that North America drives this effect in the total sample. This is supported by the fact that the North American dataset is the subset with the most observations (N=133). Thus, the results could have a great impact on the total sample. Furthermore, the results from the non-parametric test support the findings estimated by the parametric tests, further validating our results.

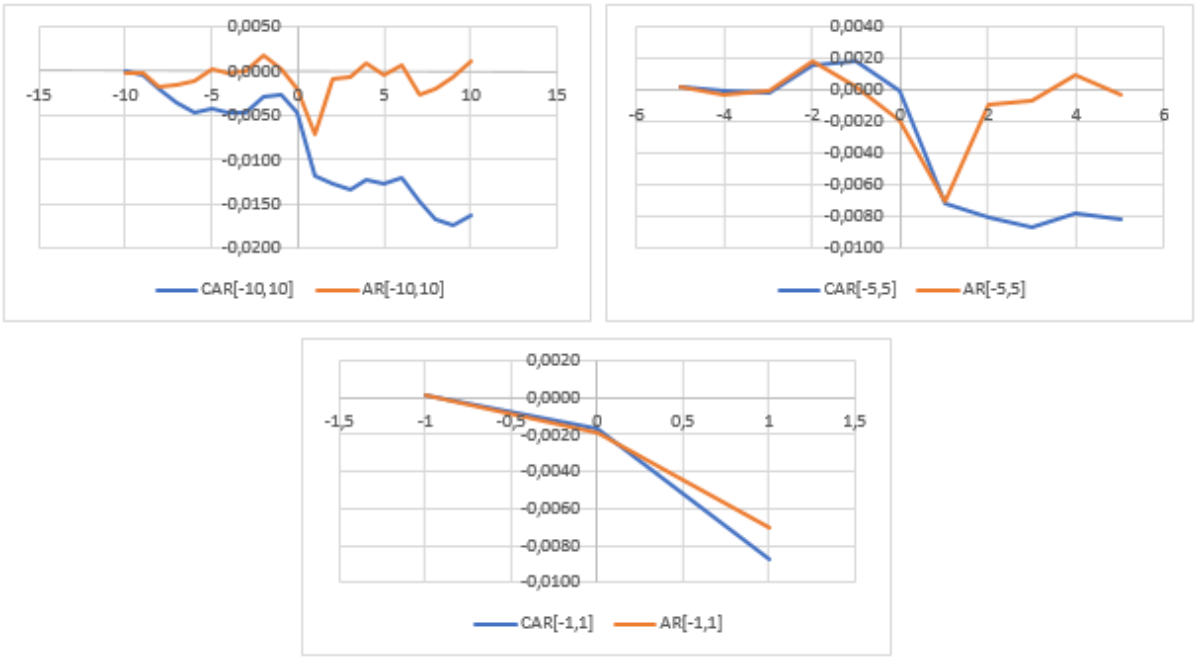

Figure 6.2: Graphical illustration of the AR and CAR development for North America
Source: Complied by authors

The sample of North America shows significant abnormal returns at the 99% confidence level for the announcement day as well as the proceeding day, with the exception of the announcement day in the [-10,10] event window where it is significant at the 95% confidence level. Nevertheless, the announcements of North American deals have an overall significant adverse effect on the abnormal returns for companies engaging in M&A transactions.

6.2.2.2 Europe

When running the test on CAR on the European subset of the total sample, we find some interesting results, where the tests show opposite results compared to those found for the total sample. Thus, the reaction on CAR is significantly positive at a 99% confidence level for all event windows. As the European subset shows the opposite effects of the total sample and North America, we have to reject *Hypothesis 2* that the significance and/or sign of the abnormal returns does not depend on the geographical location of the acquirer of the transaction. The implications of these findings will be further evaluated and explained in Section 7, *Discussion*.

Event window	CAR	T-test: CAR = 0
CAR[-1,1]	0.28%	10.4607***
CAR[-5,5]	0.71%	4.1488***
CAR[-10,10]	1.54%	5.4159***
*p < 0.1 ; **p < 0.05 ; ***p < 0.01		

Table 6.4: CAR reactions and parametric results on CAR for Europe
Source: Complied by authors

By examining the graphs in Figure 6.3, we can draw a consensus that changing the length of the event window will not have a significant impact on the results. By looking at the development of AR and CAR, it could seem like the companies engaging in merger activity tend to experience mostly positive returns around the day of the announcement, regardless of the length of the event window. When studying Appendix 9, this development is confirmed. The trend in Figure 6.3 shows that abnormal returns are significant on the day of the announcement and become even more significantly positive on the day following the announcement (with the exception of the [-10,10] event window which is only significant at a 90% confidence level the day after).

If we study the graphs and look at the day-by-day AR-figures in Appendix 9, we can observe signs of information leakage as the stock price experienced a steady increase already two days before the announcement date. Even though the AR-values prior to the event are insignificant, we observe a slight pre-announcement upwards drift in the security price, potentially resulting from leakage leading investors to drive the stock price upwards. This is consistent with Munk's (2015) findings on event studies regarding mergers and acquisitions.

Furthermore, the non-parametric sign-test mostly confirms the results generated by our parametric t-test, which further confirms our results. Based on these findings, we can conclude that the overall results of the European subset indicate that a merger announcement on average has significantly positive abnormal

returns. As this finding deviates considerably from the overall findings from the total sample, the results will be carefully considered in Section 7, *Discussion*.

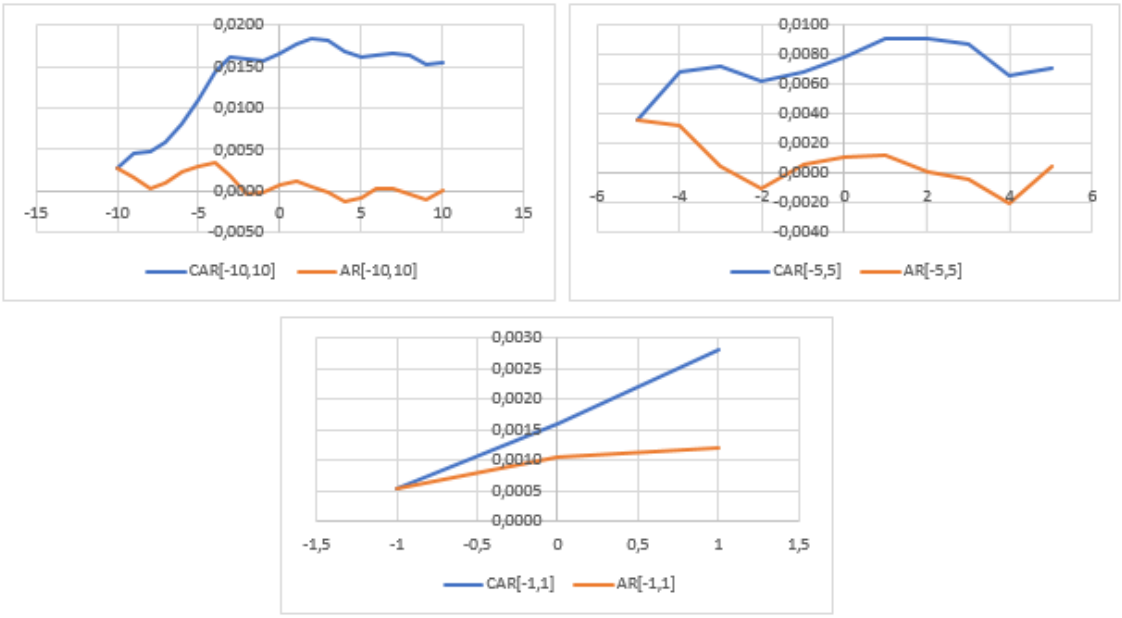

Figure 6.3: Graphical illustration of the AR and CAR development for Europe
Source: Complied by authors

6.2.2.3 Japan

Due to a low sample size of the Japanese subset (N=29), the results yielded from these tests should be carefully interpreted. Thus, we will not add too much weight on the results generated by the Japanese transactions. Regardless of the lack of significant abnormal returns, Japan shows much of the same negative trend as the total sample and the North American subset. In the smallest event window [-1, 1] we find a significant negative effect at the 1% level.

Event window	CAR	T-test: CAR = 0
CAR[-1,1]	-0.57%	-3.8349***
CAR[-5,5]	-0.13%	-1.2752
CAR[-10,10]	-0.93%	-0.334
*p < 0.1 ; **p < 0.05 ; ***p < 0.01		

Table 6.5: CAR reactions and parametric results on CAR for Japan
Source: Complied by authors

When analyzing the graphs in Figure 6.4 as well as results in Appendix 10, it is hard to find a pattern of the movement in abnormal returns around the announcement date. The AR looks like it is fluctuating greatly in both the [-10,10] and the [-5,5] event windows. It does not show any specific reaction around the actual announcement date. However, even though the sample size is relatively small, it will together with the North

American sample, drive the abnormal returns of the total sample down at the day after the announcement, offsetting the positive effect of the European transactions. Furthermore, the findings of merger announcements having an insignificant effect on abnormal returns for the two longest event windows, could imply that Japanese investors within Telecom correctly expects the event to happen. Hence, according to the longest event windows, the Japanese market could be defined as efficient. However, the low sample size makes this particular evidence relatively weak. Further research should include a larger sample size to further validate these findings and draw robust conclusions.

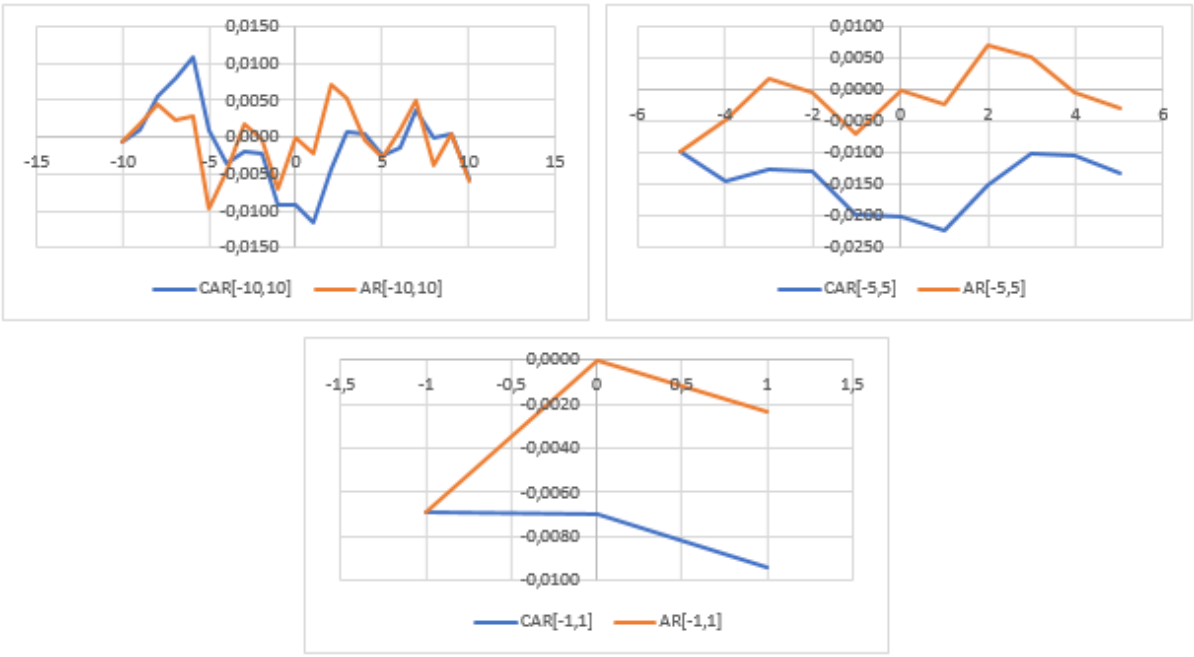

Figure 6.4: Graphical illustration of the AR and CAR development for Japan

6.2.2.4 Partial Conclusion

Based on the parametric and non-parametric test results on AR and CAR for different event windows in the various regions, we have found some interesting results. At par with the total sample, the North American sample shows a significantly negative abnormal returns for all event windows, while Europe shows the opposite effect. Even though the results of the Japanese subset are in line with those of the total sample, we will not emphasize these results due to their weak significance and low sample size.

6.3 Results from the residual analysis

Before conducting the multiple regression analysis, we will present the results of our analysis on the residuals. First, we will display a graphical illustration of the residuals on the explanatory variables. Following, we present our qualitative results on the residuals, conducting a Durbin-Watson and Breush-Godfrey test to

control for autocorrelation. In addition, we run both a Breush-Pagan and White test to ensure our dataset is heteroskedastic.

6.3.1 Graphical results

Ideally, our plot should not generally follow any clear pattern. If you can observe a trend or a pattern in the residuals, there is room for improvement regarding the required linearity of a multiple regression model. Besides, the plot should to some degree be symmetrically distributed and tend to cluster towards the middle (NIST, 2014).

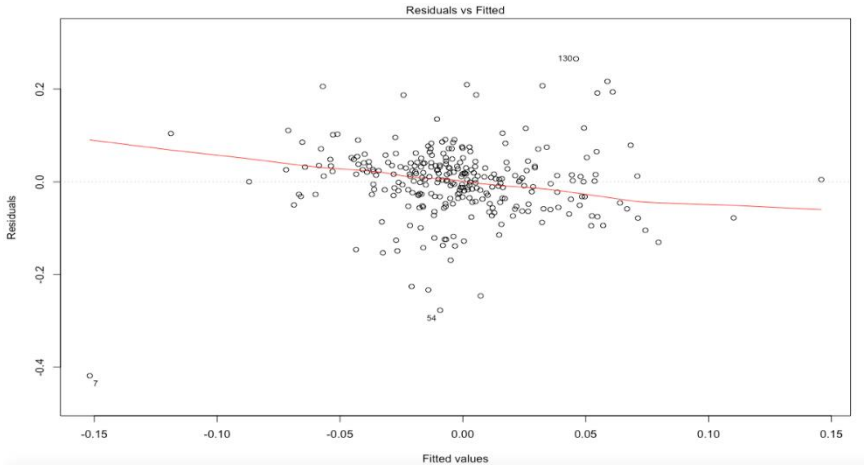

Figure 6.5: Spread-Location plot
Source: Complied by R Studio

As seen from Figure 6.5, our dataset seems to follow these requirements, supporting the use of a linear model in for this paper's analyses. However, we will complement this visual analysis with evaluating the quantitative results of autocorrelation and heteroscedasticity.

6.3.2 Quantitative results

In a linear model, such as the multiple regression model, the beta-coefficients will be biased in the presence of autocorrelation, heteroscedasticity, or both (Epps & Epps, 1977). Hence, before proceeding to the results from the multiple regression, we will provide outputs on the test on autocorrelation and heteroscedasticity.

6.3.2.1 Results for Autocorrelation

First, we applied a Durbin-Watson test for autocorrelation where the null hypothesis states that "*the errors are serially uncorrelated*". The results in Table 6.6 show that the p-value exceeds 0.05; thus, we fail to reject the null hypothesis. The variables in the sample do not have autocorrelation.

Durbin-Watson test for autocorrelation	
DW	**P-value**
2.036	0.4947
H_a = true autocorrelation is greater than zero	

Table 6.6: Results of the Durbin-Watson test for autocorrelation
Source: Complied by R studio

The results are confirmed by running a Breuch-Godfrey test with the null hypothesis that "*there is no serial correlation of any order up to p in the errors*". As expected, the BG-test confirms the findings of the DW-test as we fail to reject the null of no serial correlation.

Breusch-Godfrey test for autocorrelation		
LM-test	**df**	**P-value**
0.10489	1	0.746
H_a = the errors are serial correlated		

Table 6.7: Results of the Breusch-Godfrey test for autocorrelation
Source: Complied by R studio

6.3.2.2 Results for Heteroscedasticity

As for autocorrelation, we apply two separate tests to test for heteroscedasticity. We will start by running a Breusch-Pagan test with the null hypothesis that "*the error terms are homoscedastic*". The p-value shows a value smaller than 1%; thus, we reject the null of homoscedasticity. Therefore, the variables in our dataset are heteroscedastic, as expected.

Breusch-Pagan test for heteroscedasticity		
BP-test	**df**	**P-value**
49.784	22	0.00063
H_a = the error terms are not homoscedastic		

Table 6.8: lts of the Breusch-Pagan test for homoscedasticity
Source: Complied by R studio

As the BP-test is a test for the linear forms of heteroscedasticity, we controlled the results by conducting a White-test. The White-test is a special case of BP-tests that controls for potential non-linearity and is therefore a great estimate to validate the BP-test results. The null hypothesis of the White-test is the same as for the BP-test, and so are the results. The p-value is equal to zero. Hence, by rejecting the null hypothesis, the data sample has proven to be heteroscedastic. As the statistical software *R Studio* have the default setting of assuming homoscedastic standard errors, we had to convert our standard errors to be robust against heteroscedasticity before running the multiple regressions.

White-test for heteroscedasticity		
White-test	**df**	**P-value**
48.599	2	0.00000
H_a = the error terms are not homoscedastic		

Table 6.9: Results of the White-test for homoscedasticity
Source: Complied by R studio

6.4 Hypotheses 3, 4 and 5: Results from the multiple regressions

6.4.1 Total Sample

The following part of this section will present the results generated from our Multiple Linear Regression Models across all relevant event windows. The models will include the explanatory variables shown in Section 4, *Sample and Data*. After conducting the tests of autocorrelation and heteroscedasticity discussed above, we started out by looking at our sample as a whole, with the superior objective of rejecting *Hypothesis 3* and *Hypothesis 4*.

Hypothesis 3: The firm-specific explanatory variables have no significant effect on the abnormal returns resulting from a merger announcement.

Hypothesis 4: The deal-specific explanatory variables have no significant effect on the abnormal returns resulting from a merger announcement.

The regression results are summarized in Table 6.10, illustrating the variables of significance and their impact on the abnormal returns. Even though Table 6.10 only displays the significant variables, the full regression output can be found in Appendix 11. Following, we will present the results briefly, before we provide further discussion and interpretation of the results in Section 7, *Discussion*.

As seen from Table 6.10 there are several, both firm-specific and deal-specific factors, affecting abnormal returns. Hence, we reject *Hypothesis 3* and *Hypothesis 4* of no significant effect on abnormal returns. Furthermore, seven different variables have a significant impact on abnormal returns depending on the length of the event window. Out of the total, five variables prove to have a significant positive effect on abnormal returns, while the two others prove to affect abnormal returns negatively. As in Section 5,

Hypotheses, we have illustrated the significant variables and the sign of their impact in Figure 6.6, to make the results easier to follow.

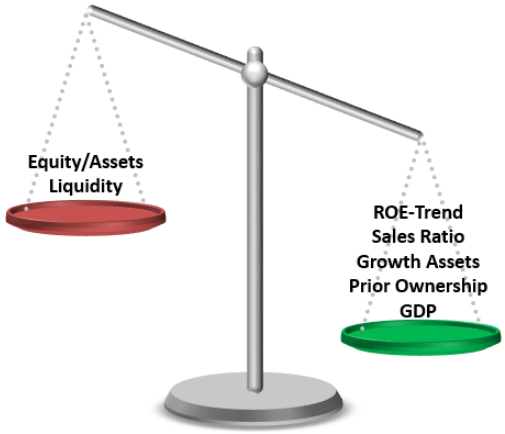

Figure 6.6: Illustration of negative (red) and positive (green) variable in the total sample

The tables presented in this section include additional information on the coefficients presented so far. At the bottom of each table we find the R-squared and Adjusted R-squared values for each model. R-squared indicates "*the proportion of the total sample variation in the dependent variable that is explained by the independent variable"* (Wooldridge, 2003). The difference between R-squared and Adjusted R-squared is that Adjusted R-squared "*penalizes additional explanatory variables by using a degrees of freedom adjustment in estimation the error variance"* (Wooldridge, 2003). Hence, when the number of independent variables increases, relative to the number of observation in the sample, the deviation between R-squared and Adjusted R-squared be more substantial. R-squared is always between zero and one, where a value closer to one indicates that the model has higher explanatory power (Wooldridge, 2003).

In Table 6.10, we observe R-squared values between 0.069 and 0.137. This means that the applied independent variables in the *Total Sample* explain from 6.9% to 13.7% of the variance in CAR. These values is quite low, indicating that there are several factors affecting CAR that are not accounted for. However, this does not necessarily mean that the models are useless. Even though the variation in CAR cannot jointly be explained by the selected variables, the results could still be reliable estimates of the effect each of the variables individually have on CAR. A low R-squared indicates that the error variance is large compared to the variance of the dependent variable. A large sample size can help offset the large error variance, and therefore create precise estimates of the partial effects of the model's variables (Wooldridge, 2003).

Additionally, the tables below also contain information on the F-statistic of each regression. These indicate the overall significance of the models. For the *Total Sample* we find all models to be statistically significant,

with results for the two shortest event windows bring significance at a 1% level, and at a 5% level in the longest event window. The significant models enable us to make comments based on the observed effects.

Starting out with the variable with the highest positive impact, we have *Sales ratio*. The variable is statistically significant at the 1% level in the two longest event windows, and at the 5% level in the [-1,1] window. For every 1% increase in the *Sales Ratio*, the acquirer's abnormal returns increase between 0.017% and 0.065% depending on the length of the event window.

TOTAL SAMPLE (N=283)

	Dependent variable:		
	CAR[-1,1]	**CAR[-5,5]**	**CAR[-10,10]**
	(1)	**(2)**	**(3)**
Firm-specific determinants			
LIQ	**-0,018***		
	(0.011)		
ROE-trend		**0.001****	
		(0.0005)	
Sales ratio	**0.017****	**0.045*****	**0.065*****
	(0.008)	**(0.016)**	**(0.019)**
Growth assets		**0.012***	0.012
		(0.007)	(0.009)
Equity/Assets	**-0.029***	**-0.064****	**-0.066***
	(0.015)	**(0.029)**	**(0.039)**
Deal-specific determinants			
Prior ownership	**0.011***	0.018	
	(0.006)	(0.011)	
External control variables			
GDP		**0.008*****	**0.009****
		(0.002)	**(0.004)**
Observations	283	283	283
R^2	0.069	0.137	0.127
Adjusted R^2	0.042	0.102	0.091
F-statistic	**2.529****	**3.913*****	**3.573*****

**p < 0.1 ; **p < 0.05 ; ***p < 0.01*

Table 6.10: Regression output for the total sample

Source: Complied by R Studio

Following, *Growth in Assets,* which is the variable with second most positive impact on abnormal returns. However, this variable is only statistically significant in one of the event windows, and only at the 10% level. In the [-5.5] window every 1% increase in assets growth increases abnormal returns by 0.012%. The *Prior*

ownership variable shows similar effects as the *Growth in Assets* as it is only significant in one of the event windows, at the 10% level. In the shortest event window, *Prior Ownership* in the target firm increases the abnormal returns of the acquirer by 0.011%. The last significantly positive variable is the control variable *GDP*, which is significant in the [-5, 5] and [-10, 10] event windows, respectively at the 1% and 5% level. In these event windows, a 1% increase in *GDP*, increase abnormal returns by respectively 0.008% and 0.009%.

With an opposite, adverse effect on abnormal returns, we find the variables *Equity to Assets* and *Liquidity.* The *Equity to Assets* ratio has the most negative impact and reduces abnormal returns between 0.029% and 0.066% for every 1% increase, dependent on the length of the event window. This variable is significant at the 5% level in the [-5, 5] window, and at the 10% level in the remaining event windows. The *Liquidity* variable is solely significant in the shortest event window where every 1% increase in the liquidity of the acquiring company, results in a 0.018% decrease in abnormal returns.

Now that we have presented the results regarding the effects of the various explanatory variables on the abnormal returns of the total sample, we want to run the same regressions on our regional subsets, with the objective of rejecting *Hypothesis 5*. As for the total sample, we look at differences and similarities across the relevant event windows and include outputs for the statistically significant variables. The complete regression outputs on all regional samples can be found in Appendices 12, 13 and 14.

Hypothesis 5: *There is no difference in factors across geographical locations in terms of significance and sign of regression coefficients.*

As outlined in Section 3, *Methodology*, we used the Kruskal-Wallis H Test to investigate whether the subsets experience significantly differences in abnormal returns. The test reveals whether potential differences in significant variables are sincere or a result of differences in abnormal returns in the different subsets. As deliberated in the *Methodology* section, the null hypothesis expresses that the subsets originate from an identical population, which would imply that the mean abnormal return of each subset is equal. We ran the test three times, one for each event window.

The tests showed chi-squared statistics of 5.5969, 1.159 and 3.2598, with corresponding significant levels of 0.1004, 0.5602 and 0.196. The complete output from the tests can be found in Appendix 15. Given these results, we are unable to reject the null hypothesis. We can therefore conclude that the different subsets are

drawn from an identical population. Hence, any disparity found between the subsets is not a result of differences in the types of firms in the various geographic regions, nor that investors favor one region over another.

6.4.2 North America

With 133 observations, the North American subset consists of almost half of our total sample. Table 6.11 show that five of our variables positively affect the abnormal returns of acquirers in North America, while three variables have a negative impact, further illustrated by Figure 6.7. We observe R-squared values between 0.17 and 0.319. This is high compared to the *Total Sample,* indicating that it is favorable to divide the total sample into subgroups based on geographical regions. We also recognize that all the models are statistically significant at the 1% level, indicated by the F-statistics.

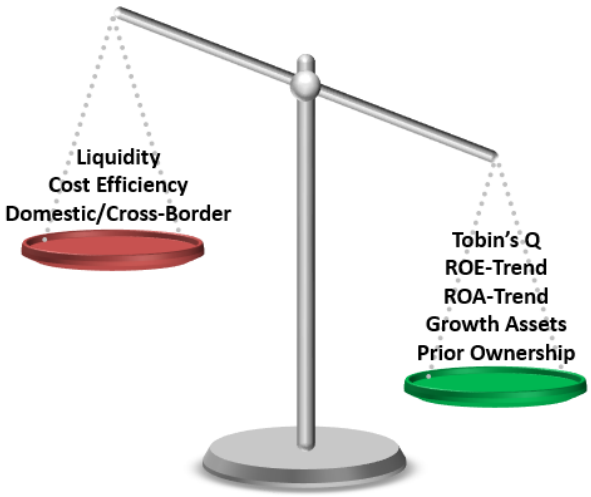

Figure 6.7: Illustration of negative (red) and positive (green) variables in North America

From Table 6.11, we observe that the variable with the most substantial positive beta-coefficient and, thus, impact on abnormal returns, to be *Growth in Assets*. This variable is statistically significant at the 1% and 5% level in the [-10, 10] and [-5, 5] windows, where every 1% increase causes an increase in abnormal returns between 0.033% and 0.043%. Furthermore, *Tobin's Q* is statistically significant and positive in the two shortest event windows, increasing abnormal returns with between 0.036% and 0.034%, respectively.

Another variable affecting the abnormal returns positively for acquirers in North America is *Prior Ownership*. Acquiring firms having an initial stake in their target company prior to the announcement, increases the abnormal returns with 0.019%. The effect is significant at the 5% level in the [-1, 1] event window. The two

remaining variables with a positive impact on abnormal returns of North American acquirers are *ROA-Trend* and *ROE-Trend*. They boost abnormal returns between 0.001% and 0.005% contingent on the length of the event window. *ROA-Trend* is statistically significant at the 10% level in the longest window, while *ROE-Trend* is significant at the 1% and 5% level in the two shortest event windows.

NORTH AMERICA (N=133)			
	Dependent variable:		
	CAR[-1,1] (1)	CAR[-5,5] (2)	CAR[-10,10] (3)
Firm-specific determinants			
Q	**0.036** (0.014)**	**0.034** (0.020)**	0.040 (0.025)
ROE-trend	**0.001*** (0.0003)**	**0.002** (0.001)**	
LIQ			**-0.035** (0.021)**
ROA-trend			**0.005*** (0.002)**
Cost efficiency		**-0.122** (0.068)**	**-0.153** (0.071)**
Growth assets		**0.033** (0.015)**	**0.043*** (0.016)**
Deal-specific determinants			
Domestic/Cross-Border	-0.048 (0.034)	-0.048 (0.039)	**-0.074** (0.045)**
Prior ownership	**0.019** (0.010)**	0.030 (0.023)	0.008 (0.006)
Observations	133	133	133
R^2	0.17	0.276	0.319
Adjusted R^2	0.116	0.217	0.251
F-statistic	**3.173***	**4.653***	**4.685***

**p < 0.1 ; **p < 0.05 ; ***p < 0.01*

Table 6.11: Regression output of North America

Source: Complied by R Studio

Furthermore, the three variables *Cost Efficiency, Domestic/Cross-Border* and *Liquidity* show a significant negative impact on abnormal returns. The variable with the greatest negative impact is *Cost Efficiency* which is statistically significant at the 10% and 5% level in the two longest event windows. The variable indicates that every 1% increase in cost efficiency reduces abnormal returns by 0.122% and 0.153%. Second, we have the *Domestic/Cross-Border* variable, which is negative with an effect of 0.074%, only significant at the 10% level in the longest event window. This effect suggests that cross-border deals have a negative impact on

abnormal returns relative to domestic transactions. The third and last variable with a negative and significant impact in North America is the *Liquidity* where a 1% increase reduces abnormal returns by 0.035%

6.4.3 Europe

The second largest subset, with 121 observations, represents the European region. As observed from Table 6.12 and Figure 6.8, we found five variables with a significantly positive and four variables with a significantly adverse effect on abnormal returns. As for the previous samples, the distribution is illustrated in Figure 6.8. The European subset experiences the same positive effects of dividing the total sample as observed for North America. Compared to R-square values of around 0.10 in the *Total Sample,* we find values between 0.265 and 0.309 in Europe. The F-statistics also show statistically significant values, all at the 1% level.

Figure 6.8: Illustration of negative (red) and positive (green) variables in Europe

We found the *Sales Ratio* to be the variable with the largest significantly positive impact. The variable is statistically significant at the 1% level across all event windows. Hence, an increase in *Sales Ratio* of 1%, boosts abnormal returns between 0.035% and 0.1%, depending on the length of the event window. Further, *Cost Efficiency* is found to have the second largest positive impact on abnormal returns. The variable is statistically significant at the 5% and 1% level in the shortest and longest event windows. Abnormal returns grow between 0.013% and 0.041% per 1% increase in *Cost Efficiency*.

The third positive variable is the control variable *M&A Wave*, statistically significant in the [-10,10] window at the 1% level. Every 1% increase in *M&A Wave,* increases abnormal returns by 0.037%. *Sales Trend* is also found to have a positive impact, statistically significant at the 1% level in the longest event window and the 5% level in the [-5,5] window. Abnormal returns increase by 0.039% and 0.025%, respectively. The last

variable to have a positive impact on European acquirers is *GDP*. However, the variable is only significant in the [-5,5] event window at the 5% level. The coefficient indicates that a 1% increase in *GDP* raises abnormal returns by 0.005%.

EUROPE (N=121)			
	Dependent variable:		
	CAR[-1,1] (1)	CAR[-5,5] (2)	CAR[-10,10] (3)
Firm-specific determinants			
LIQ	**-0.027*** (0.014)		
ROA-trend			**-0.004*** (0.001)**
Sales ratio	**0.035*** (0.012)**	**0.078*** (0.012)**	**0.100*** (0.017)**
Cost efficiency	**0.013** (0.006)**		**0.041*** (0.014)**
Equity/Assets	**-0.028* (0.016)**		
Sales trend		**0.025** (0.012)**	
Deal-specific determinants			
Payment1	**-0.037*** (0.014)**	-0.032 (0.020)	**-0.064** (0.030)**
External control variables			
GDP		**0.005** (0.002)**	
M&A Wave			**0.037*** (0.013)**
Observations	121	121	121
R^2	0.265	0.301	0.309
Adjusted R^2	0.198	0.251	0.253
F-statistic	**3.969***	**6.030***	**5.504***

**p < 0.1 ; **p < 0.05 ; ***p < 0.01*

Table 6.12: Regression output of Europe

Source: Complied by R Studio

Results show that there are three firm-specific and one deal-specific variable that affect abnormal returns negatively. The variable with the most negative impact is Payment1, representing shares as the method of payment. The variable is statistically significant at the 1% and 5% level in the shortest and longest event windows. The effect indicates that transactions having shares as the primary source of payment decrease abnormal returns by between 0.037% and 0.064% in their respective event windows. Furthermore, the firm-

specific variables, *Liquidity* and *Equity to Assets* ratios are very similar in both impact and level of significance, with both being solely significant in the [-1, 1] window, at the 10% significance level, with values of -0.027% and -0.028%, respectively. The last firm-specific variable of interest is the *ROA-Trend*. The variable is highly significant, at the 1% level, and reduces abnormal returns by 0.004% per percentage increase.

6.4.4 Japan

The final geographic region in our sample is Japan. As previously mentioned, the Japan subset only consists of 29 observations. Given the low number of observations, and the high number of variables, the results presented in Table 6.13 are less comparable to the other subsets of this thesis. In spite of this, we have decided to present the results of the Japanese subset, since it affects the overall sample. The results above may give an indication of the effects in Japan, but a larger sample would increase the validity of the results.

Table 6.13 shows eleven statistically significant variables, mostly firm-specific with supplements from deal-specific and control variables. This distribution is consistent with the other subsets we have investigated. By looking at the F-statistic, which indicates the significance of the overall model, we see that the model on the event window [-5,5] is statistically insignificant. For this reason, we decide only to comment on the variables in the [-1,1] and [-10,10] windows. Within these event windows, we find five variables with a significant positive impact, while six variables show the opposite effect, further illustrated by Figure 6.9.

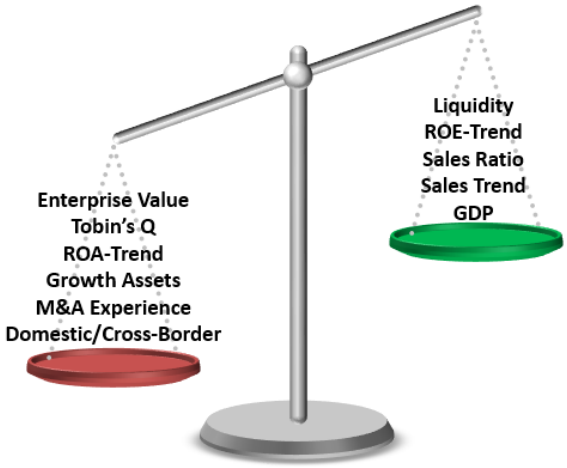

Figure 6.9: Illustration of negative (red) and positive (green) variables in Japan

First, we observe that *Liquidity* has the greatest positive effect on abnormal returns, although only significant at the 10% level. Hence, every 1% increase in *Liquidity* increases abnormal returns with 0.334%. The variable *Sales Trend* has the second largest positive impact with 0.252% per percentage increase and a level of

significance at 5%. Further, the *Sales Ratio* variable is highly significant and has a positive impact of just above 0.2%. The last firm-specific variable with a positive influence on abnormal returns is *ROE-Trend*, where a 1% increase, improves the abnormal returns with 0.151% at a 5% significance level. In addition to the aforementioned firm-specific variables, we also find the control variable *GDP* affecting abnormal returns. With a significance at the 1% level, abnormal returns increase with 0.012% and 0.019% for every percentage increase in *GDP* depended on the length of the event window.

When addressing the variables with negative effects in Table 6.13, we find *ROA-Trend* and *Growth in Assets* to be dominating. With the variables being significant at 5% and 1% respectively, our results indicate a decrease in abnormal returns of 0.179% and 0.119% per percent increase in the aforementioned variables. Additionally, we find one deal-specific variable of significance, specifically the dummy on *Domestic/Cross-border*. Showing a negative value of 0.074% in the [-1, 1] window, the effect suggests that engaging in cross-border transactions has a negative impact on abnormal returns in Japan.

Two other variables with comparable negative effects are *Tobin's Q* and *Merger Experience*. *Tobin's Q* is significant at the 1% level in the longest event window, while *Merger Experience* is only significant in the shortest event window at the 10% level. The two variables show negative values of 0.046% and 0.038% respectively. The last variable of interest is *Enterprise Value*. The highly significant and negative value of 0.018% indicates a negative relationship between firm size and abnormal returns in Japan.

The R-squared values witnessed in the Japanese subset are surprisingly high compared to those in the other subsets, with values between 0.665 and 0.69. However, in the other subsets, the difference between the R-square and the Adjusted R-squared values is relatively low. In Japan, this gap is quite large, especially in the [-5,5] window with a difference of 0.384. As previously mentioned, the Adjusted R-squared penalizes additional explanatory variables, and this is more visible in Japan that the other subsets given the low number of observations. However, the high R-squared values also indicate that in the observations we have, the independent variables explain a relatively large proportion of the variance in CAR. Nevertheless, this has to be further examined with a larger sample size before drawing definite conclusions.

The F-statistics reveal that only two of the models, those with the shortest and longest event windows, are statistically significant at the 5% and 1% levels respectively. The model which represents the [-5,5] window is found to be insignificant. As a result, we are unable to discuss the findings in this model even though three of the variables are found to be significant.

JAPAN (N=29)			
	Dependent variable:		
	CAR[-1,1] (1)	CAR[-5,5] (2)	CAR[-10,10] (3)
Firm-specific determinants			
Enterprise Value	**-0.018*** (0.005)**		
Q		-0.004 (0.016)	**-0.046*** (0.013)**
LIQ	0.061 (0.129)	**0.395** (0.167)**	**0.334* (0.182)**
ROE-trend	**0.151** (0.068)**		
ROA-trend	**-0.179** (0.070)**	-0.075 (0.079)	
Sales-trend	**0.252** (0,111)**		
Sales ratio		**0.197** (0.082)**	**0.203*** (0.062)**
Growth assets	**-0.119*** (0.045)**	-0.018 (0.073)	
M&A Experience	**-0.038* (0.021)**		
Deal-specific determinants			
Domestic/Cross-Border	**-0.074*** (0.023)**	-0.016 (0.036)	-0.024 (0.031)
External control variables			
GDP	**0.012*** (0.003)**	**0.018*** (0.007)**	**0.019*** (0.006)**
Observations	29	29	29
R^2	0.69	0.668	0.665
Adjusted R^2	0.457	0.284	0.506
F-statistic	**2.965**	1.741	**4.190***

**p < 0.1 ; **p < 0.05 ; ***p < 0.01*

Table 6.13: Regression output of Japan

Source: Complied by R Studio

6.4.5 Partial conclusion regression results

As can be seen from Table 6.10 above there are several factors, both firm-specific and deal-specific, affecting abnormal returns; hence, Hypothesis 3 and Hypothesis 4 are rejected. In the total sample together with all the subsets combined, we find 16 variables that significantly affect abnormal returns. Out of these 16, eight show consistent results, while the rest depend on the sub-sample being analyzed. Based on the significant difference between the geographic regions, we can reject H*ypothesis* 5. As a result, we can conclude that there are in fact differences in the geographical regions regarding which factors significantly affect abnormal returns. Next, we will further elaborate and interpret the implication of the results presented in this section.

7.0 Discussion

This section presents a descriptive analysis of the study where we will discuss and elaborate the results and compare them to earlier empirical findings. In addition, we will deliberate the implications of the findings in light of general economic theory. As for the results, we will structure this section by following the five different hypotheses introduced in Section 5. Elaborating and potentially rejecting the hypotheses will help us draw a consensus about the thesis. The goal is to explain how an announcement of M&A transactions affect the shareholders of companies globally, and whether regional differences affect the result of the global sample.

7.1 Hypothesis 1 and 2: Elaborating the results of AR and CAR

7.1.1 Hypothesis 1: AR and CAR for the total sample

Hypothesis 1: *The AR and CAR are not significantly different from zero in the three symmetric event windows [-1, 1],[-5,5] and [-10,10]*

Going into detail on the implications of our results of CAR for the total sample, demands a comparison of our results relative to the results of earlier findings in the same area. Our dataset contains deals from the G10 countries, we therefore assume that our sample to includes enough countries to be defined as global. This way we can compare our findings with other, similar studies done on a global scale. Most event studies investigating the global effects on acquirer's abnormal returns around the announcement day conclude with either significantly negative or insignificantly abnormal returns. This is shown through the studies deliberated in the literature review where Park et al. (2002) and Bruner (2004) reported negative market reactions regarding the acquirer's stock returns around the announcement date of a merger. Furthermore, Rieck (2002) did not find any significant abnormal returns in the overall impact of international telecom transactions.

Event window	CAR	T-test: CAR = 0
CAR[-1,1]	-0.39%	-12.2377***
CAR[-5,5]	-0.23%	-3.5667***
CAR[-10,10]	-0.19%	-1.6768*
*p < 0.1 ; **p < 0.05 ; ***p < 0.01		

Table 6.2: CAR reactions and parametric results on CAR for the total sample
Source: Complied by authors

The results yielded from our study, as shown in Table 6.2, demonstrate significantly adverse effects on the shareholder value following an M&A transaction. This finding is in line with earlier empirical evidence on global studies, as the majority of similar studies confirm the negative effect on stock returns around the announcement day. Rejecting *Hypothesis 1* of mergers having no significant impact on returns therefore seems reasonable.

According to the semi-strong form of the efficient market hypothesis prices should reflect all publicly available information and historical data. Thus, the rare existence of abnormal returns should not be present for the market to be efficient. We can therefore say that as the merger announcement yields significant abnormal returns, the telecommunication market is not considered efficient. The question here would be whether or not investors have realistic expectations regarding merger announcements. If we had failed to reject our null hypotheses of *Hypothesis 1,* AR = 0 and CAR = 0, this would have been a sign of the stock being priced correctly and the mergers being realistically expected by the investors.

For the total sample, statistical significance is found at day 0 and day 1 (or just one of them) for all event windows. Thus, *Hypothesis 1* of no impact was rejected, indicating unrealistic investor expectations. The deviation between the actual EPS and the forecasted EPS is the reason for the existence of abnormal returns. Hence, the perception and behavior of the investors can result in either underestimating or overestimating the effects of merger announcements. The observed negative abnormal returns throughout the event period of all event windows demonstrates the fact that the stock market, on average, has been too optimistic in their expectations of the effects of merger announcements.

7.1.2 Hypothesis 2: AR and CAR for each region

Hypothesis 2: *The significance or signs of AR and CAR is not dependent on geographical location*

To make the discussion concerning Hypothesis 2 easy to follow, we have divided it into the same structure as the previous section, presenting the empirical discussion for each region separately before providing a comparison at the end of this subsection. Studies that isolate the effects of transactions within the telecom industry to solely one specific region, have proven hard to find. Hence, the region-specific findings have to be compared to general M&A findings within each region. The basis of comparison will, for this reason, be

weaker than what we optimally would have wanted to present, but nevertheless, we believe that it still provides some perspective on our findings.

7.1.2.1 North America

Event window	CAR	T-test: CAR = 0
CAR[-1,1]	-0.88%	-7.9269***
CAR[-5,5]	-0.81%	-3.6493***
CAR[-10,10]	-1.62%	-4.5699***
*p < 0.1 ; **p < 0.05 ; ***p < 0.01		

Table 6.3: CAR reactions and parametric results on CAR for North America
Source: Complied by authors

The available empirical evidence on event studies regarding reactions in abnormal returns following merger announcements of North American acquirers is widespread, especially for the United States. However, even though the region is a popular analysis-object, event studies isolating solely North America tend to analyze all merger announcements within the region instead of narrowing their scope to one specific industry. The results will therefore be discussed in light of previous, general literature on abnormal returns reactions caused by merger announcements in the United States and Canada.

Our results show similar results compared to the total sample, suggesting that North America could possibly be the region driving the total sample's overall aggregated figures. Our results reflect a significantly negative abnormal returns for all event windows, roughly consistent with prior literature. Even though Wilcox et al. (2001) found merger announcements to increase the market values of the acquirer, other literature on the North American countries primarily states the opposite. Kiyamaz and Baker's (2008) study on North America showed that the bidding firm's announcement returns on average are significantly negative, giving further validation to our results. Similarly, Moeller et al. (2005) find acquisition announcements between 1998 and 2001 to be costly for acquiring shareholders generating negative abnormal returns. Comparable findings on abnormal returns around merger announcements in North America confirm the reasonability of our results (Healy, Palepu, & Ruback, 1992) (Eckbo & Thorburn, 2009).

Furthermore, the results are supported by the findings of Grinstein and Hribar from 2003 who find that M&A transactions in which CEOs have more power suffer from significantly negative abnormal returns of -3,8%. Their paper emphasizes the finding of CEOs receiving lucrative cash compensations for the successful completion of M&A deals. The compensations are obtained in spite of the findings that acquiring firms do not profit from these deals (Jensen & Ruback, 1983). Studies within corporate governance provide evidence

of American CEOs receiving overall higher compensations compared to European countries (Georgen & Renneboog, 2004).

The direct costs of these deal bonuses given to CEOs of the acquiring firms seem small in light of the potential indirect costs they entail. Nevertheless, if the management has the power to affect board decisions, they will choose to maximize their own value rather than shareholder value. The sizeable abnormal returns found by Grinstein and Hribar (2003), suggest that economic losses surrounding an M&A deal could be caused by CEOs self-dealing perks.

Besides, several papers have shown evidence of Free Cash Flow (FCF) being frequently applied for managerial empire building (Moeller et al., 2005) (Franks, Harris, & Titman, 1991) (Andrade et al., 2001). Thus, the compensation scheme of North American M&A deals could potentially be part of an explanation of the negative abnormal returns occurring around the announcement date within the region. Furthermore, the findings are consistent with the non-maximizing merger motives by Berk and DeMarzo (2013) presented in the *Literature Review*. Hence, previous literature confirms the finding of a reduction in the stock price of the acquirer following a non-value maximizing merger (Berk and DeMarzo, 2013).

7.1.2.2 Europe

Event window	CAR	T-test: CAR = 0
CAR[-1,1]	+0.28%	10.4607***
CAR[-5,5]	+0.71%	4.1488***
CAR[-10,10]	+1.54%	5.4159***
*p < 0.1 ; **p < 0.05 ; ***p < 0.01		

Table 6.4: CAR reactions and parametric results on CAR for Europe
Source: Complied by authors

At first glance, the results found in the European sample are surprising, because they contradict all other results found in this thesis. The effect yielded by the European deals appears to be the reason for the deviations between the t-statistics of the total sample and North America. Even though Europe produces different results compared to the other regions, the findings are supported by earlier research. The study conducted by Georgen and Renneboog (2004) found that European acquirers' stock prices had a slight positive reaction to M&A announcements. Furthermore, they found that the positive effect was mainly driven by the UK deals which generated significantly higher abnormal returns compared to their European counterparts. In our dataset, deals from the United Kingdom constitute approximately 20% of our European deals, and could therefore help in explaining the positive returns.

The findings of Ingham, Kran and Lovestam (1992) further confirm the theory that the UK constitutes parts of the driving force for the positive abnormal returns observed for our European dataset. Through a survey involving executives from 146 large UK firms, they found that 77% expected increased short run profitability around the announcement date. This qualitative review limits the assertions one can make but offers results similar to scientific, quantitative studies (Ingham et al., 1992). Taken together, this previous empirical evidence enables us to further validate the results generated by our analysis on CAR.

Studies of Dilshad (2013) support these findings through their investigation of M&A deals from 2001-2010. They find signs of information leakage, rumors or insider trading, resulting in the rise of the stock price prior to the announcement. Bringing back the graphs in Figure 6.3, we can see that the same signs of leakage are present in our dataset, further validating the reasonability of our AR-results.

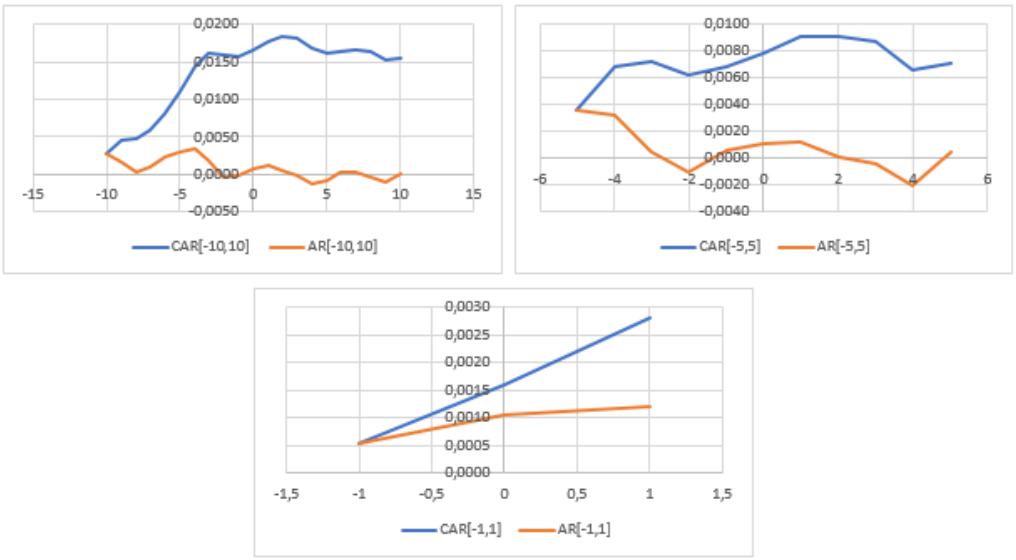

Figure 6.3: Graphical illustration of the AR and CAR development for Europe
Source: Complied by authors

Regardless of Dilshad's elaboration that the positive net present value of these transactions is relatively short-lived, the [-5, 5] event window show positive gains. It is not before the event window is extended to [-30, 30] that the data failed to provide significant abnormal returns (Dilshad, 2013). As our objective is solely to investigate the short-term effects on the stock price of the acquiring firms, we are not able to comment on the longer-term effects of merger announcements on stock prices. However, this would be interesting to investigate in future studies.

Furthermore, there are several other determinants of share price reactions to consider when explaining the movement in abnormal returns. A study by Raua and Vermaelen (1998) show that a merger between value-firms tend to yield higher abnormal returns compared to growth companies. Hence, companies with a low market-to-book ratio generate higher abnormal returns compared to firms with a high market-to-book ratio, which has proven to yield substantial negative abnormal returns (Raua & Vermaelen, 1998). In the second part of the discussion, we will use Tobin's Q as an independent variable in our multiple regression analysis to investigate the effect, if any, of this phenomenon in our dataset. The primary objective of running numerous regressions on our dataset is to identify variables that could help us explain the deviation of abnormal returns we observe across our subset of regions.

It is also imperative to evaluate the potential differences between the eight countries within the European subset. According to Moschieri and Campa (2017), important differences among European countries can still explain patterns tied to M&A transactions. Their analysis suggests that the dissimilarity between the European countries arises from unique institutional characteristics ingrained in the corporate structure of companies in each country. Hence, when aggregating all European observations in one sample, it becomes difficult to differentiate and unveil the internal differences within the European nations involved (Moschieri & Campa, 2017).

7.1.2.3 Japan

Event window	CAR	T-test: CAR = 0
CAR[-1,1]	-0.57%	-3.8349***
CAR[-5,5]	-0.13%	-1.2752
CAR[-10,10]	-0.93%	-0.334
*p < 0.1 ; **p < 0.05 ; ***p < 0.01		

Table 6.4: CAR reactions and parametric results on CAR for Japan
Source: Complied by authors

The low sample size of Japanese deals (N=29), makes the results provided by this subset less reliable. However, we will provide some insight on our results compared to those of earlier empirical studies, as Japan affects the overall aggregated total sample. As seen from the Table 6.4, the only significant abnormal returns occur in the [-1, 1] event window. Longer event windows show an insignificant M&A announcement reaction. This finding is consistent with Shah and Arora (2014) who fail to reject their null hypothesis of abnormal returns being significantly different from zero. Additionally, these results are consistent with other researchers like Swaminathan et al. (2008), Papadatos (2010) and Aintablian & Roberts (2005).

The [-1, 1] event window shows a significantly negative abnormal returns around the merger announcement date. It is difficult to differentiate whether this is the result of inaccuracy caused by having a small sample size, or if the market overvalues merger announcements in the telecommunication industry in Japan. Even though our sample does not have enough observation to draw a conclusion, this area of investigation could be interesting to look into in future studies.

Overall, our results are somewhat surprising, showing substantial differences in abnormal returns across regions. However, we have to acknowledge that the quantitative nature of the event study methodology does not take into account important aspects such as behavioral finance and potential irrational expectations of the investors. Hence, when investors receive new information, they do not necessarily update their beliefs correctly, contradicting Bayes' theorem of conditional probability (Barberis & Thaler, 2003). In the last few years, it has become apparent that the classical economic theory of EMH and the theory of rational expectations are inadequate in explaining specific outcomes. The focus has shifted towards the psychology of economics, introducing alternative interpretations of empirical research surrounding events like merger announcements (Daniel, Hirschleifer, & Subrahmanyam, 1998) (Barberis, Shleifer, & Vishny, 1998).

As presented by DeBondt and Thaler (1985) and Jegadeesh and Titman (1993), key heuristics to behavioral finance, such as *conservatism*, *underreaction*, *overreaction* and *investor sentiment to news announcements* have undoubtedly rejected the theory of fully rational behavior. Doukas and Petmezas (2007) posit that overconfidence exhibits to managers who "*underestimate (overestimate) the risks (synergy gains) associated with mergers*" (Doukas & Petmezas, 2007). Hence, the results of our analysis could just as easily have been due to differences in investors' perceptions of merger announcements. A possible explanation of the deviations could be that North American investors generally are over-optimistic prior to the event, while European investors have lower expectations towards the profitability of the upcoming merger. Hence, the deviations between the expected and the realized returns would become negative in North America and positive in Europe. Even though these factors have not been included in our econometric analysis, it presents an interesting area of investigation for future research. To provide a better overview, we will present our findings together with earlier empirical findings in the same area in Table 7.1, displayed on the following page.

Study	CAR	Sample Size	Sample Period	Event Window	Notes
Our study shows:					
Total Sample	-0.39%*** -0.23%*** -0.19%*	283	1996-2016	[-1,1] [-5,5] [-10,10]	M&A in telecom in the G10 countries
North America	-1.62%*** -0.81%*** -0.88%***	133	1996-2016	[-1,1] [-5,5] [-10,10]	M&A in telecom in North America
Europe	0.28%*** 0.71%*** 1.54%***	121	1996-2016	[-1,1] [-5,5] [-10,10]	M&A in telecom in Europe
Japan	-0.93%***	29	1996-2016	[-1,1]	M&A in telecom in Japan
Earlier empirical findings show:					
Eckbo, Thorbum (2000)	-0.30%	390	1964-83	[-40,0]	US acquirers Canadian targets
Healy, Palepu & Ruback (1992)	-2,2%*	50	1979-84	[-5,5]	50 largest US mergers during period
Asquith, Bruner & Mullins (1983)	+3.48%**	170	1963-79	[-20,1]	Mergers only, daily data
Kohers and Kohers (2000)	+1.37%** +1.09%** +1.26%	961 673 1634	1987-1996	[0,1]	Sample of mergers among high tech firms (divided into cash, stock deals and whole sample)
Myeong Park et al. (2002)	-5.1%*	42	1997-2000	[-5,5]	Using 42 transactions in the telecom industry worldwide
Dodd (1980)	-1.24%	66	1970-77	[-1,0]	Mergers only, daily data
Olaf Rieck (2002)	+0.17%	72	N/A	[-10,10]	Investigates CAR for international telecom mergers (market model)
Wilcox et.al	+0.335%***	88	N/A	[-1,0]	Valuation of mergers and acquisitions in the telecommunications industry
Moeller et al. (2005)	-0.69%	729	1998-2001	[-1,1]	Using the market model to test for gain/loss for acquiring firm shareholders
Grinstein & Hribar (2003)	-3.8%**	327	1993-99	NA	Checks the effect of CEO power on abnormal returns
Georgen & Renneboog (2004)	+0.7%*	41	1993-2000	[-2,2]	Investigates short-term wealth effects of large intra-European takeover bids
Dilshad (2013)	+2.7%*	18	2001-2010	[-5,5]	M&A announcement effects on stock prices in Europe using the market model
Shah & Arora (2013)	-1.2% -1.7% -2.5%	37	2013	[-2,2] [-5,5] [-10,10]	Examines M&A announcements in the Asia-Pacific region
*p < 0.1 ; **p < 0.05 ; ***p < 0.01					

Table 7.1: Overview of our results as well as results from previous empirical findings

Source: Complied by authors

After finishing this first part of the discussion, it is evident that some questions remain to be answered. So far, we have analyzed the AR and CAR generated from the market model estimation in the different event windows across data subsets and ended up with rejecting both *Hypothesis 1* and *Hypothesis 2*. In the next section, we will aim to explain which variables, if any, affect these changes in abnormal returns around the merger announcement dates, by answering the remaining hypotheses. Analyzing how firm-specific and deal-specific variables affect the cumulative abnormal returns in different event windows can potentially provide us with some further insight.

7.2 Hypotheses 3, 4 and 5: Elaborating the results of the regression analysis

In this part of the discussion, we will go through the regression analysis variable by variable and compare the results outlined in Section 6, *Results,* with our initial expectations, and results found in previous studies. We will make comparisons between the total sample and the different subsets, and describe the differences presented in the *Results*. We will start out by discussing the firm-specific variables, then the deal-specific, and finally the external control variables.

7.2.1 Firm-Specific Variables

As displayed in Section 4, *Sample and Data*, we included 11 firm-specific variables to capture the effect of different company-specific determinants. Some of these exhibited results as expected, while others contradicted our initial hypotheses. We will now discuss the results and implication of these findings.

The Liquidity variable is found to be negative and statistically significant in one of the event windows in both the total sample and the European subset. This is conflicting with our initial guess and the results of Kirchoff and Schiereck (2011). An increase in *Liquidity* originates from an increase in the free cash flow (FCF) to sales ratio. A growth in FCF indicates that a company can invest their excess cash, by either acquiring another company, paying dividends or through stock repurchase. A possible explanation for this negative reaction on abnormal returns is the liquidity effect discussed by Liu and Yeh (2014). The effect indicates that low-liquidity stocks have a possibility of being compensated by higher return rates. Thus, the liquidity of a firm could be considered as an attribution of overreaction (Liu & Yeh, 2014).

Additionally, Amihud and Mendelson (1986, 1989) claimed that investing in companies with lower access to excess cash introduces a higher risk. Hence, leading to an allocation of premiums to investors as a compensation for taking on additional risk. In line with our findings, they found that companies with lower liquidity generated positive abnormal returns (Wang , Lu, & Hsu, 2012). Thus, even though high liquidity is

equivalent to high solidity and a company in good health, this is not always reflected in the stock price. It could also indicate that the company is too risk-averse and that investors want the company to invest a greater amount of their excess cash to further maximizing profitability.

The variables *ROE-Trend* and *ROA-Trend* were also initially hypothesized to have a positive impact on abnormal returns. By starting out with *ROE-Trend*, we find it to be positive and significant in the total sample, as well as in the subsets North America and Japan. This is in line with our expectations and confirms that investors view a growth in ROE positively. The results on *ROA-Trend*, on the other hand, are quite interesting, showing a positive and significant effect in North America, but an adverse and significant effect in Europe and Japan. The results in North America are in line with our expectations. However, the findings in especially Europe, but also Japan, are surprising. The considerable negative impact in Japan could be explained by the small sample size, and further analysis with a higher number of observations have to be conducted to increase the validity of these results.

To explain the different effects in North America and Europe, we have to closely examine the relationship between return on assets and abnormal returns. An increase in ROA indicates a greater increase in net income relative to total assets. A higher ROA would logically be viewed as a good sign, given the indication of higher profits on lower level of investment. This can explain the effect we observe in North America. However, the increase in net income has to be funded by either debt or equity. The formula does not say anything about the method of financing, and this has to be further examined to get the full picture. If financed by debt, the risk of the company would increase, which could be view negatively from investors' point of view. Previous studies have found European investors to be more risk-averse than their American counterparts (Enskog, 2015) (Scorbureanu & Holzhausen, 2011). Based on this, a higher risk aversion from European investors could be another explanation of the negative impact seen in the European subset.

When it comes to the variables *Sales Ratio* and *Sales Trend* explaining the revenue-to-assets ratio and the revenue development, respectively, the results are as expected. *Sales Ratio* shows positive and significant coefficients in the total sample, Europe and Japan, while *Sales Trend* does the same in Japan. The variable *Sales Ratio* could also be considered as an asset turnover ratio, which indicates the overall performance of a company. An increase in this ratio expresses higher performance, and it is therefore natural that an increase in *Sales Ratio* results in higher abnormal returns. The positive impact of *Sales Trend* shows that the firms that are able to increase their revenues are rewarded with positive abnormal returns. This is in line with the findings of Reddy, Qamar & Yahanpath (2017).

The equity ratio is negative in the total sample, as well as for both Europe and North America, however not statistically significant for North America. This contradicts our expectations of a positive connection. Usually, an increase in the level of equity relative to the total assets indicates less risk and greater financial strength of a company. However, the interpretation of the negative relation between abnormal returns and equity ratio generated in our results, have a logical explanation. The *Equity Ratio* is a useful indicator of the level of leverage of the acquiring companies in this thesis. A decrease in the ratio could yield positive signals towards the stockholders as long as the company earns a return on assets (ROA) that exceeds the interest paid to creditors (Berk & DeMarzo, 2013).

Traditional models within corporate finance suggest that companies adjust their capital structure by evaluating the trade-off between the incentive benefits of debt financing against its costs of financial distress (Hovakimian, Opler, & Titman, 2001). Hence, the negative relation between *CAR* and the *Equity Ratio* across all regional samples may suggest that investors perceive the capital structure of Telecom companies being non-optimal. That is, operating with a debt level that does not optimally exploit the advantages of financing their investments with debt.

All variables discussed so far evaluate historical numbers when determining the profitability of a company. *Tobin's Q* however, indicates the expectations related to forthcoming development (Kirchhoff & Schiereck, 2011). We expected *Tobin's Q* to have a positive and statistically significant effect. Our expectations are met in the North American subset, which shows that investors are positive to acquirers with high-quality management, generating a high market-to-book value. This relation is supported by the findings of Morck, Schleifer and Vishny (1990) and Lang, Stulz and Walkling (1989) who found that poor past performance and low-quality management decrease the acquirer's returns.

In Japan, the opposite effect on Tobin's Q is evident, as the relation to abnormal returns is negative and significant. This could be because companies with low market-to-book values prior to merger announcements have a far greater benefit of reaping the potential synergy effects following a merger. If the acquiring firm is initially poorly managed, the restructuring of both management and assets that follows such transactions could be seen as positive, since it can improve the initial value of the company. Investors would therefore view an increase in Tobin's Q as a negative sign, as this would decrease the possibility for obtaining the much-needed restructuring that follows such a transaction. Both Madura and Wiant (1994) and Raua and Vermaelen (1998) found the same effect from the market to book ratio in their studies, giving support to the results found in Japan.

The variable *M&A Experience* was found to be statistically significant solely in Japan. Contrary to our expectations, the relation to abnormal returns is negative. We would assume that prior M&A experience would be seen as positive from an investor's point of view. However, our results indicate otherwise. The weakness of this variable is that it does not reflect the success rate of the previous experience, but only signalizes its occurrence. The negative effect on abnormal returns could be explained by former mergers being unsuccessful within the Japanese companies included in our sample. However, this has to be further analyzed to draw a definite conclusion. Higgins and Rodriguez (2006) found the same negative impact of merger experience in their study in the pharmaceutical industry, strengthening our interpretation of the results.

Cost Efficiency shows interesting and somewhat surprising results. Even though expected to have a positive effect on abnormal returns, we are only able to find this in Europe. In North America, an increase in *Cost Efficiency* has a negative impact on abnormal returns. Both of these findings are statistically significant. An increase in *Cost Efficiency* tells us that operational costs have risen compared to the previous year. However, an increase in operational costs by itself is not necessarily a bad thing, as it could stem from a boost in revenues that increase profits. Therefore, isolating cost efficiency does not tell us what caused the increase, which could explain the deviating results in Europe and North America. Eltivia, Sudarma, Rosidi & Saraswati (2014) researched the impact of *Cost Efficiency* on abnormal returns. They find that *Cost Efficiency* has a surprisingly limited impact on abnormal returns, only explaining 0.022% of the total variance. They further support their results of the variable's low explanatory power by emphasizing the investor's interest in profits, rather than the isolated effect of costs (Eltivia et al., 2014).

When looking at the variable *Growth in Assets*, we find a significant and positive result for both the Total Sample and the North American subset. Besides, we observe a negative and significant result in Japan. In line with the studies of Fu (2011) and Cooper et al. (2009), we expected a negative connection, like the one found in Japan. The positive effects observed in the total sample and North America can be explained by the findings of Cao (2015) whose results indicate that the effect on abnormal returns depend on the type of asset growth. Cooper et al. (2009) solely focus on the left-hand side of the balance sheet, without regard to the right-hand side. Cao (2015) stresses the importance of looking at the source of financing that drives the growth, and splits assets into groups depending on how they were financed. Explicitly, he categorizes the assets into three groups; (1) financed by debt, (2) financed by equity, and (3) financed by operating liabilities (suppliers). Specifically, he finds that growth in assets financed by suppliers is associated with positive future performance. Cao explains this effect by emphasizing that suppliers may have superior information gained

through private information channels as a result of their close connection to the firm, that the other groups of financing may not have access to. A potential explanation to our results is therefore that the companies in our sample, particularly in North America, experience growth in assets financed by suppliers and therefore positively influence abnormal returns.

Finally, the last firm-specific variable included in our analysis is *Enterprise Value*, which we hypothesized to have a negative impact on abnormal returns. The significant result found in the Japanese subset confirms this hypothesis. In addition, the result is the same as those found by Kirchhoff and Schiereck (2011) and Higgins and Rodriguez (2006) in their studies of the pharmaceutical industry. Nevertheless, since this variable is only significant in Japan, with only 29 observations, this needs further analysis to draw a general inference. Future research could include an additional variable to investigate the relative size of the acquirer compared to the target. In line with previous literature, it would have been interesting to check whether differences in size between target and acquirer could affect the abnormal returns obtained.

7.2.2 Deal-Specific Variables

We included four deal-specific variables in our analysis with the aim of investigating whether the different nature of the deals influenced abnormal returns. As for the firm-specific variables, some of the deal-specific showed results in line with our expectations, while others did not. The different results will now be closely examined.

Out of the four deal-specific variables, we will start by discussing the dummy variable separating *Related and Unrelated Mergers.* We were unable to establish any significant relationship between the type of merger and abnormal returns. Previous studies have found consistent results, showing that related mergers earn greater abnormal returns, giving little support of the effect of diversification in unrelated mergers (Wilcox et al., 2001) (Georgen & Renneboog, 2004) (Seth, 1990). As previously mentioned, we are not able to comment on these types of differences in our dataset.

Our second deal-specific variable illustrates the *Method of Payment* and is found to be statistically significant and negative in Europe. This is in line with our expectations and symbolizes how investors negatively perceive mergers that are financed with stocks instead of cash. This result is supported by several previous studies, which further validate the theory that transactions paid in cash generate higher abnormal returns than those paid with shares (Andrade et al., 2001) (Asquith et al., 1987) (Yook, 2003).

Our third deal-specific variable is *Prior Ownership*, which we assumed to have a positive effect on abnormal returns. This is supported by our findings with positive and significant results in both the total sample and in North America. In addition to our study, several other papers have found a similar positive effect, backing the theory that having an ownership stake in the target prior to the merger announcement is viewed positively by investors (Frame & Lastrapes, 1998) (Yang, 2014).

The final deal-specific variable tests whether transactions are defined as *Domestic* or as *Cross-Border*. A cross-border deal can be part of a diversification tactic but can face difficulties related to cultural differences. As hypothesized previously, the variable is found to be negative and significant in the North America and Japan subsets. This suggests that investors believe that the cultural challenges outweigh the potential diversification benefits and prefer domestic M&A compared to international. This is consistent with previous empirical findings, supported by Campa & Hernando (2004), Rieck (2002) and Park et al. (2002), increasing the reliability of our results.

7.2.3 External Control Variables

Besides the mentioned firm-specific and deal-specific variables, we have included three external control variables to control for macroeconomic trends and investigate whether external factors affect abnormal returns. As these variables are given, as well as impossible for a company's management to control for, we will place limited emphasis on them. However, they indicate how management can look at macroeconomic trends to maximize the timing of the announcement and are therefore of interest when discussing the overall effect of merger announcements.

The first control variable is the *M&A Wave Position*. This variable expresses the timing of the announcement relative to overall merger waves in the industry. According to our expectations, announcements close to the peak of a merger wave experience lower abnormal returns given the increased competition in the industry and a higher premium on target firms. Our results indicate otherwise. We find a positive and significant result in Europe, which is the only dataset with a significant result. A possible explanation for this finding is that during merger waves, investors could generally be more positive towards M&A than outside waves. As outlined by Harford (2005) merger waves happen as a result of shocks in the economy that increase the need for asset reallocation. Given a sufficient level of liquidity, firms will carry out the needed changes through M&A. The positive impact of M&A waves could therefore be due to investors believing that the need for reallocation of assets increases the synergy potential.

The second control variable is *GDP* which is found to be positive in all samples, however not significantly significant in America. This demonstrates that it is favorable to announce mergers and acquisitions in periods of economic growth compared to recessions. This is in line with our hypothesized effect. Lastly, we have included the control variable *Interest Rate* which is supposed to control for variations in the cost of capital. Even though we hypothesized this variable to have a negative impact on abnormal returns, the variable did not show any significant values in any of the datasets applied in this thesis.

7.2.4 Partial conclusion

This section has revealed that some of the results of our analysis are in line with our expectations and the findings of previous studies, while others are not. One example of a variable with values different from our expectations is *Liquidity,* which was found to be negative. This indicates that firms with a high amount of excess cash generate lower abnormal returns, potentially because of the low risk, and therefore premium, obtained by investors investing in cash-rich firms. Another example of a variable with values that contradict our hypotheses is *Equity Ratio.* It was found to be negative, possibly because of a higher return on assets than the interest rate, which makes it favorable to finance with debt compared to equity.

Besides the variables that showed the same contradicting results in all subsets, we found several variables that exhibited conflicting values in different subsets, indicating that the change in one variable can be viewed differently by investors depending on their origin. One example is *ROA-Trend* showing positive values in North America and negative in Europe and Japan, possibly illustrating higher risk-aversion in Europe and Japan than in North America. Another variable that displayed contradicting values was *Tobin's Q*, with positive effects in North America but a negative impact in Japan. The conflicting results can illustrate that while American investors value companies with high-quality management, their Japanese counterparts see a higher potential for synergies in companies with a low *Tobin's Q*. Furthermore, *Cost Efficiency* was found to be positive in Europe and negative in North America. The observed difference could indicate that American investors put greater emphasis on cost reduction and that European investors are more driven by profits.

8.0 Limitations

As with most research papers, this thesis has some limitations. This section will provide a brief discussion of these limitations.

Several of these limitations are inherent to the event study methodology but aggravated by the fact that our data sample only consists of companies within the telecommunication industry. First, the rare existence of an efficient stock market is a strong assumption, especially regarding telecommunication companies prior to the burst of the dot-com bubble in 2000, and thereafter. Second, international telecom mergers are frequently subject to multiple regulatory approvals, making it harder to both identify the exact announcement date and avoid information leakage and rumors biasing the results. In our thesis, we assume the market to be semi-efficient, thus assuming that investors use all historical and publicly available information to make their decisions. Including the independent variable, *Prior Ownership,* enables us to control for whether having an initial stake in the target, and thus possess a higher level of due diligence prior to the merger, offers any advantages for the acquiring firm.

When choosing to include deals from several different countries, we have a new set of limitations due to the international context. Since we are investigating the aggregated market reaction of multiple firms from different countries, bias can be present due to the securities not being traded on the same stock market. Furthermore, even though we started out with nearly 600 observations, the final sample consisted of only 283 observations. This reduction of our dataset had to be done as the databases available only provided fundamental data and stock price information on some of the companies. Additionally, the cofounding events we had to remove constituted almost one-third of our original sample. Despite this, we do not believe that we would be able to enlarge our sample, as the strict regulations on merger activity delimited the number of transactions prior to the 1990s (Warf, 2003). Hence, we believe, based on the obtainable resources, that we adequately cover the largest possible sample size.

We based our choice of applying the market model to measure normal performance on the fact that most similar papers on M&A announcements had done the same, which makes the results easier to compare. We could potentially have included other similar models, e.g., the constant mean return model, as a further validation and robustness check of the output yielded by the market model. However, the time frame and the page number requirement of this thesis limits the option of conducting additional analyses. Besides, as previous, similar studies are unanimous in applying solely one model when calculating normal returns, we see limited value of checking our estimates with other normal return models.

Another limitation concerns the variables included in our multiple regression analysis and how it is subject to the likelihood of omitted variable bias. There are without a doubt room for including additional independent variables which will affect the returns in some way. However, we were not able to include all the variables we desired without running into problems with multicollinearity. Besides, our study is highly quantitative. Hence, whether or not it would have been desirable to include qualitative variables in the analysis remains unknown due to our limited time-span and expertise. Although we are aware that there is more literature that potentially could have been covered, we believe that regardless of the restrictions imposed, our thesis covers highly relevant literature taking into consideration the scope of this paper, as well as the time available.

In addition, a limitation relevant to the empirical validity of our model is the aforementioned possibility of multicollinearity (Stock and Watson, 2015). There is a possibility that two or more variables may be wrongly inferred to be casually related to each other, without this being the case. Thus, we have to evaluate the possibility of this phenomenon called spurious correlation, where a third factor, outside the model, could be correlated with two of the factors applied in our regression (Stock and Watson, 2015). To control for multicollinearity, we created a correlation matrix to identify which variables to exclude based on the correlation. Thus, although there will still exist some spuriously correlated, exogenous variables, we have controlled for collinearity to the best of our ability.

Furthermore, we have to acknowledge the potential weakness resulting from our dataset being drawn from multiple countries with multiple different exchange rates. Due to missing financial data in Datastream, and missing stock data in Compustat, we had to combine different databases to maximize our sample size. We started out by extracting the reported ISO (International Organization for Standardization) currency code; the three-letter codes representing various currencies applied throughout the world. By assuming these codes to correspond across databases, allowed us to observe deviations of exchange rates across databases. Furthermore, we withdrew daily exchange rates from Datastream, and converted the relevant rates to match the stock prices with the financial figures. Withdrawing data from multiple different sources without having the time or capacity to cross-reference every number, increases the possibility of errors. This is also true because all numbers reported into the databases are done by humans. Thus, the probability of human errors could potentially affect the validity and reliability of the data applied in the analysis.

There are also limitations tied to variables that we were unable to define and include due to their complexity. For example, it would have been interesting to add a variable on the relative size and values between the

target and the acquirer. Even though these variable are highly quantifiable, we had limited access to data for unlisted targets, prohibiting us from finding the right financial data to warrant including such variable in the analyses. As previously mentioned, there are other factors that could have been interesting to investigate, e.g. examining the perspective from behavioral finance and how investor's sentiment affects the reaction in abnormal return following an M&A announcement. However, these factors would demand a more qualitative methodology in potential future studies.

Overall, future extensions of this research should aim at using a more extensive dataset, include a larger and/or different set of independent variables, as well as refining the treatment of how horizontal, vertical and conglomerate merger are differentiated. Additionally, as discussed in this paper, the results generated from the Japanese subset will in future studies demand a larger sample size in order to draw general conclusions within the region. Lastly, increasing the size of the event window to investigate the effects of the merger announcements could be an interesting extension to review the long-term effects, and thereby draw more accurate conclusion about the realized synergy effects of the merger.

9.0 Conclusions

This thesis has analyzed the general effects of mergers and acquisitions within the telecommunication industry in the period between 01.01.1998 and 31.12.2016. The aim was to test if the semi-strong form of the efficient market hypothesis holds in the case of M&A announcements. Additionally, we have investigated the effect and magnitude of three types of factors; firm-specific, deal-specific and external control factors. Our sample consisted of 283 deals, including 72 firms located in 11 countries.

By comparing event study methodology suggested by various researchers, we combined different elements and constructed a six-step process to be followed in the analysis. We used daily firm and index data and applied the market model to calculate normal returns. Our global approach enabled us to comment on trends in the Telecom industry worldwide. Furthermore, to check whether the potential effects were driven by one geographic region or if the effects were the same in every market, we split the 11 countries into three groups for which separate analyses were conducted.

We outlined two hypotheses, *Hypothesis 1* and *2,* which aimed to answer our main research question about the semi-strong form of the efficient market hypothesis. Based on the analysis of the general effects, we found robust evidence supporting that M&A announcements have a significant effect on abnormal returns. Thus, we rejected *Hypothesis 1* and conclude that the market is not semi-strong efficient. *Hypothesis 2* intended to discover whether there were any differences across geographical regions. The analysis revealed significant differences, with negative abnormal returns in North America and to some extent Japan, while the effects were positive in Europe. Hence, we were able to reject *Hypothesis 2*. The significant effects found in each geographic region gives further support to the conclusion that the Telecom market is not semi-strong efficient. The only exceptions are the two longest event windows in the Japanese subset where we were unable to find any significant effect, suggesting an efficient market.

The second part of the analysis consisted of a regression analysis with the goal of testing the second research question; whether any firm- and/or deal-specific variables affect abnormal returns, or if these differ depending on the acquirer's geographic region. To answer these questions, we composed *Hypotheses 3* to *5*. Our results revealed several factors, both firm-specific and deal-specific, affecting abnormal returns; thus, *Hypotheses 3* and *4* were rejected. Furthermore, we found considerable differences in terms of both significant variables and their magnitude in the different subsets. Based on this, we were able to reject *Hypothesis 5,* and thus prove that there are differences in which factors affect abnormal returns in different geographical regions.

There is limited previous literature analyzing the effects different factors have on abnormal returns in the Telecom industry, both globally and in specific markets. Our region-based approach enables us to draw comparisons between markets, and thus contribute to and fill some of the gap in empirical studies comparing the general effect M&A announcements and different firm-specific and deal-specific factors have on abnormal returns. Our findings indicate that differences found are the result of contradicting views of investors in regard to several factors, as well as their expectations toward mergers and acquisitions.

Based on our results we conclude that there are several factors, both firm-specific and deal-specific, the management of the acquiring firm can examine before conducting a merger to maximize their returns. Given the high number of mergers and acquisitions observed in the Telecom industry over the last two decades we believe this to be highly relevant. We hope that this thesis can provide the industry with useful information about the factors that can help them achieve positive returns. By conducting similar studies, future research could further validate our results. They should also investigate whether the same effects are present with the use of additional factors, such as different characteristics of the target as well as qualitative factors. This would give valuable insight, and further minimize the lack of empirical research on the subject.

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Appendix

Appendix 1: *A selection of different event study steps from the empirical literature*

# of steps	Steps	Source
7	8. Event definition 9. Selection criteria 10. Normal and abnormal returns 11. Estimation procedure 12. Testing procedure 13. Empirical results 14. Interpretation and conclusion	Campbell, Lo and MacKinley (1997)
5	6. Define event date 7. Characterize normal returns 8. Calculate excess returns 9. Aggregate excess returns 10. Run statistical tests	Henderson (1990)
3	4. Identify relevant transactions 5. Calculate cumulated abnormal returns 6. Test statistical significance of CARs	Kirchhoff and Schiereck (2011)
4	1. Cleaning data and calculating the event and estimation windows 2. Estimating normal performance 3. Abnormal and cumulative abnormal performance 4. Test for significance	Data and Statistical Services (2007)
5	6.0 Identify the event of interest 7.0 Model the security and price reaction 8.0 Estimate the excess returns 9.0 Organize and group excess returns 10.0 Analyze results using statistical significance tests	Bouwman (1983)
5	1. Determine dates 2. Calculate expected returns 3. Measure abnormal returns 4. Organize and accumulate the abnormal returns 5. Analyze and statistically test the abnormal returns	Patricksson and Evans (2016)
8	1. Exactly define the event 2. Define the same and news sources 3. Identify the exact event date 4. Drop confounding events 5. Compose the event list and retrieve asset price data 6. Determine the estimation method for expected return calculation 7. Determine the estimation and event window 8. Calculate the cumulative (average) abnormal return or buy-and-hold abnormal returns	Event Study Metrics (n.d.)

Appendix 2: *Example of regression output from selection of market indices*

	Dependent variable:				
	AMERICAN.TOWER				
	(1)	(2)	(3)	(4)	(5)
MSCI.WORLD	1.275***				
	(0.041)				
S.P.GLOBAL.1200		1.264***			
		(0.040)			
NASDAQ.TELECOM			0.776***		
			(0.021)		
S.P.GLOBAL.1200.TELECOM				1.113***	
				(0.037)	
NYSE.COMPOSITE					1.078***
					(0.034)
Constant	0.001	0.001	0.001*	0.001*	0.001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Observations	4,845	4,845	4,845	4,845	4,845
R2	0.168	0.173	0.215	0.155	0.170
Adjusted R2	0.168	0.173	0.215	0.155	0.170
Residual Std. Error (df = 4843)	0.029	0.029	0.028	0.029	0.029
F Statistic (df = 1; 4843)	979.012***	1,015.580***	1,328.918***	887.963***	991.318***
Note:					*p<0.1; **p<0.05; ***p<0.01

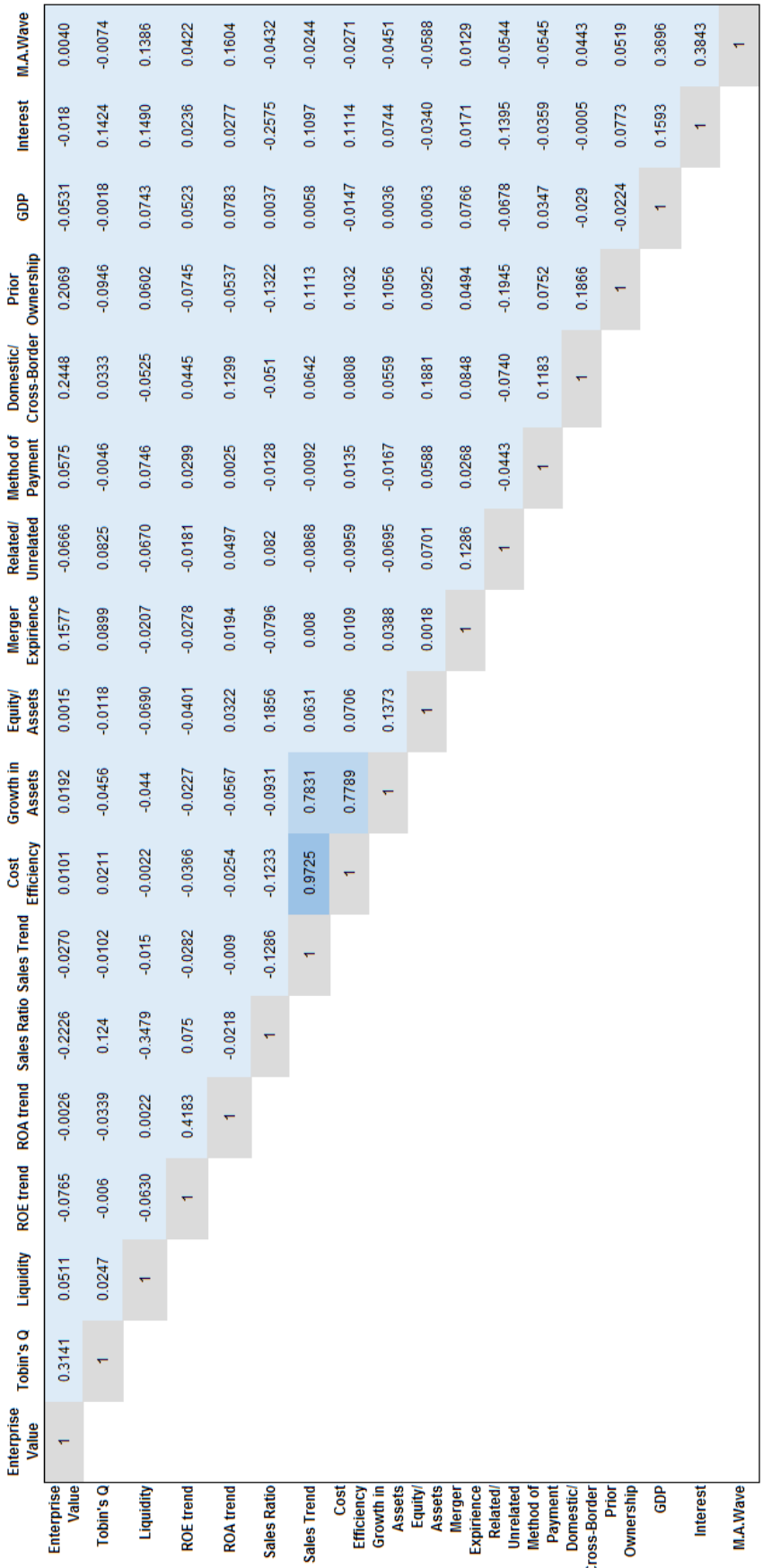
	Dependent variable:				
	NTT.DOCOMO.INC				
	(1)	(2)	(3)	(4)	(5)
MSCI.WORLD	0.319***				
	(0.030)				
S.P.GLOBAL.1200		0.294***			
		(0.029)			
NASDAQ.TELECOM			0.058***		
			(0.016)		
S.P.GLOBAL.1200.TELECOM				0.430***	
				(0.027)	
NIKKEI.225.STOCK.AVERAGE					0.733***
					(0.017)
Constant	0.0002	0.0002	0.0003	0.0003	0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	4,746	4,746	4,746	4,746	4,746
R2	0.024	0.021	0.003	0.052	0.273
Adjusted R2	0.024	0.021	0.003	0.052	0.273
Residual Std. Error (df = 4744)	0.021	0.021	0.021	0.020	0.018
F Statistic (df = 1; 4744)	115.266***	102.096***	13.054***	262.277***	1,779.277***
Note:					*p<0.1; **p<0.05; ***p<0.01

Appendix 3: *List of Companies Sample Encompasses*

Company Name	**UK 2007 SIC**	**Headquarters**
A3 Allmanna	61100	Sweden
Adept Telecom PLC	61100	United Kingdom
Afone SA	61100	France
Altice NV	61100	Netherlands
American Tower Corporation	61200	United States
AOL Time Warner Inc	61900	United States
AT&T Inc	61900	United States
ATN International Inc	61200	United States
BCE Inc	61100	Canada
BT Group PLC	61100	United Kingdom
Calamp Corporation	61200	United States
Cartesian	61100	United States
Centurylink Inc	61100	United States
Cincinntati Bell Inc	61100	United States
Cogeco Cable Inc	61100	Canada
Comcast Corporatation	61100	United States
Consilidated Communiations Holdings Inc	61200	United States
Crown Castle International Corporation	61200	United States
Deutsche Telekom AG	61100	Germany
Dun and Bradstreet Corporation	61900	United States
Eckoh Technologies PLC	61900	United Kingdom
Ecotel Communication AG	61900	Germany
Eutelsat Communications SA	61300	France
Frontier Communications Corporation	61100	United States
Global Eagle Entertainment	61200	United States
Hawaiian Telecom Holdco Inc	61100	United States
HC2 Holdings Inc	61100	United States
IDT Corporation	61100	United States
Iliad SA	61100	France
Inmarsat PLC	61300	United Kingdom
Internet Initiative Japan Inc.	61100	Japan
Japan Communications Inc.	61200	Japan
Jubii Europe	61900	Netherlands
KCOM Group PLC.	61100	UK
KDDI Corporation	61200	Japan
Koninklijke KPN NV	61100	Netherlands
Liberty Global PLC	61100	United Kingdom
LICT	61100	United States
Mitel Networks Corporation	61200	Canada
Nippon Telegraph & Telephone Corporation	61900	Japan

NTT Docomo Inc	61200	Japan
Orange SA	61100	France
Orbcomm Inc.	61300	United States
Pegasus Communication Corporation	61100	United States
Proximus SA	61100	Belgium
Quebecor Inc.	61900	Canada
Rogers Communications Inc.	61200	Canada
SBA Communication Corporation	61200	United States
Shaw Communications Inc.	61100	Canada
Shenandoah Telecommunications Company	61200	United States
Sky Perfect JSAT Corporation	61300	Japan
Softbank Group Corporation	61200	Japan
Softbank Technology Group	61200	Japan
So-net M3 Inc	61900	Japan
SPOK	61200	United States
Swisscom AG	61100	Switzerland
Tele2 AB	61100	Sweden
Telecom Italia SPA	61100	Italy
Telefonica Deutschland Holding AG	61100	Germany
Telenet Group Holding NV	61100	Belgium
Telephone & Data Systems Inc.	61200	United States
Telia Company AB	61200	Sweden
Telus Corporation	61100	Canada
Tiscali SPA	61200	Italy
United Inc.	61900	Japan
United Internet AG	61100	Japan
United States Cellular Corporation	61200	United States
Verizon Communications Inc.	61900	United States
Vivendi SA	61100	France
Vodafone Group PLC	61200	United Kingdom
Windstream Corporation	61100	United States
Zayo Group Holdings Inc	61200	United States

Appendix 4: *Correlation matrix of the explanatory variables applied in the multiple regression*



	Enterprise Value	Tobin's Q	Liquidity	ROE trend	ROA trend	Sales Ratio	Sales Trend	Cost Efficiency	Growth in Assets	Equity/ Assets	Merger Expirience	Related/ Unrelated	Method of Payment	Domestic/ Cross-Border	Prior Ownership	GDP	Interest	M.A.Wave
Enterprise Value	1	0.3141	0.0511	-0.0765	-0.0026	-0.2226	-0.0270	0.0101	0.0192	0.0015	0.1577	-0.0666	0.0575	0.2448	0.2069	-0.0531	-0.018	0.0040
Tobin's Q		1	0.0247	-0.006	-0.0339	0.124	-0.0102	0.0211	-0.0456	-0.0118	0.0899	0.0825	-0.0046	0.0333	-0.0946	-0.0018	0.1424	-0.0074
Liquidity			1	-0.0630	0.0022	-0.3479	-0.015	-0.0022	-0.044	-0.0690	-0.0207	-0.0670	0.0746	-0.0525	0.0602	0.0743	0.1490	0.1386
ROE trend				1	0.4183	0.075	-0.0282	-0.0366	-0.0227	-0.0401	-0.0278	-0.0181	0.0299	0.0445	-0.0745	0.0523	0.0236	0.0422
ROA trend					1	-0.0218	-0.009	-0.0254	-0.0567	0.0322	0.0194	0.0497	0.0025	0.1299	-0.0537	0.0783	0.0277	0.1604
Sales Ratio						1	-0.1286	-0.1233	-0.0931	0.1856	-0.0796	0.082	-0.0128	-0.051	-0.1322	0.0037	-0.2575	-0.0432
Sales Trend							1	0.9725	0.7831	0.0631	0.008	-0.0868	-0.0092	0.0642	0.1113	0.0058	0.1097	-0.0244
Cost Efficiency								1	0.7789	0.0706	0.0109	-0.0959	0.0135	0.0808	0.1032	-0.0147	0.1114	-0.0271
Growth in Assets									1	0.1373	0.0388	-0.0695	-0.0167	0.0559	0.1056	0.0036	0.0744	-0.0451
Equity/ Assets										1	0.0018	0.0701	0.0588	0.1881	0.0925	0.0063	-0.0340	-0.0588
Merger Expirience											1	0.1286	0.0268	0.0848	0.0494	0.0766	0.0171	0.0129
Related/ Unrelated												1	-0.0443	-0.0740	-0.1945	-0.0678	-0.1395	-0.0544
Method of Payment													1	0.1183	0.0752	0.0347	-0.0359	-0.0545
Domestic/ Cross-Border														1	0.1866	-0.029	-0.0005	0.0443
Prior Ownership															1	-0.0224	0.0773	0.0519
GDP																1	0.1593	0.3696
Interest																	1	0.3843
M.A.Wave																		1

Appendix 5: *Alpha and Betas for CAR [-5, 5]. We have chosen to include the values of the regression coefficient for solely the [-5, 5] event window, for illustrative reasons. However, the values for the [-1, 1] and [-10, 10] event windows can be found on the USB-stick.*

Date	Company	Alpha	Beta
01-05-2015	ADEPT TELECOM PLC	0.0037643	-0.4953
09-08-2004	AFONE SA	-0.0002214	0.10843
13-02-2013	A3 ALLMANNA IT	-0.0015273	0.41274
17-11-2016	A3 ALLMANNA IT	-0.0010923	0.12256
20-05-2015	ALTICE NV	0.0049716	0.83139
14-10-2016	ALTICE NV	0.0009697	1.11298
02-11-2001	AMERICAN TOWER CORPORATION	-0.0018711	0.87568
10-12-2002	AMERICAN TOWER CORPORATION	0.0051353	1.00817
04-05-2005	AMERICAN TOWER CORPORATION	0.0005227	0.47036
02-06-2009	AMERICAN TOWER CORPORATION	0.0000419	0.75879
29-10-2009	AMERICAN TOWER CORPORATION	0.0002817	0.77747
05-03-2001	TIME WARNER INC.	0.0010362	0.58138
07-01-2002	TIME WARNER INC.	-0.0015556	0.84979
22-08-2002	TIME WARNER INC.	-0.0015944	0.9131
19-05-2003	TIME WARNER INC.	-0.0022312	0.92818
22-02-2000	AT&T INC.	-0.0043347	1.1088
18-10-2001	AT&T INC.	0.0021111	0.72469
31-01-2005	AT&T INC.	-0.0010498	1.06207
06-03-2006	AT&T INC.	0.0012353	0.62236
29-06-2007	AT&T INC.	0.0001446	0.94066
11-05-2009	AT&T INC.	0.0001445	1.20299
02-08-2012	AT&T INC.	0.0010577	0.80232
12-07-2013	AT&T INC.	-0.0000841	0.96097
19-05-2014	AT&T INC.	0.0000812	0.93335
26-01-2015	AT&T INC.	-0.0001848	0.93633
26-07-2005	ATN INTERNATIONAL	-0.0009757	0.15385
22-12-2005	ATN INTERNATIONAL	0.0027037	0.18564
11-11-2002	BCE INC.	0.0007247	0.4852
06-05-2004	BCE INC.	-0.0009291	0.17445
10-09-2010	BCE INC.	0.0006709	0.26334
16-03-2012	BCE INC.	0.0005084	0.12459
23-07-2014	BCE INC.	0.0001786	0.44682
02-05-2016	BCE INC.	-0.0001195	0.42139
27-06-2002	BT GROUP PLC	0.0012584	1.23173
19-12-2003	BT GROUP PLC	-0.0011149	0.78542
16-09-2004	BT GROUP PLC	0.0002294	0.59295
31-10-2005	BT GROUP PLC	-0.0001513	0.95359
01-02-2007	BT GROUP PLC	0.0017485	0.68846
06-07-2007	BT GROUP PLC	0.0002914	0.73883
09-07-2008	BT GROUP PLC	-0.0011562	0.82066
05-02-2015	BT GROUP PLC	0.0007336	0.7204
09-05-2006	CALAMP CORPORATION	0.0010136	0.66259
20-12-2012	CALAMP CORPORATION	0.0013414	0.5186
01-02-2016	CALAMP CORPORATION	0.001114	0.9632
06-03-2002	CARTESIAN	-0.0002278	0.55849
30-12-2002	CENTURYLINK INC.	0.0015543	1.06096
19-08-2003	CENTURYLINK INC.	0.0004629	1.10884
02-03-2005	CENTURYLINK INC.	-0.0001075	0.92154
18-12-2006	CENTURYLINK INC.	0.0008859	0.43406

Date	Company	Alpha	Beta
27-10-2008	CENTURYLINK INC.	0.0025672	0.68768
22-04-2010	CENTURYLINK INC.	0.0003228	0.5735
27-04-2011	CENTURYLINK INC.	-0.0005348	0.61181
31-10-2016	CENTURYLINK INC.	-0.0007858	0.95636
06-12-2007	CINCINNATI BELL INC.	-0.0012038	0.68972
12-05-2010	CINCINNATI BELL INC.	0.0002374	0.73994
02-06-2006	COGECO CABLE INC.	0.0017256	-0.403
13-06-2008	COGECO CABLE INC.	-0.0003848	0.55053
18-07-2012	COGECO CABLE INC.	-0.0007631	0.40295
18-02-1999	COMCAST CORPORATION	0.0003563	0.81305
01-05-2001	COMCAST CORPORATION	0.0011619	0.23922
19-12-2001	COMCAST CORPORATION	0.0005798	0.28167
25-03-2004	COMCAST CORPORATION	-0.0012807	0.80359
31-10-2005	COMCAST CORPORATION	-0.0014363	0.69369
27-11-2006	COMCAST CORPORATION	0.001605	0.37556
14-05-2008	COMCAST CORPORATION	0.0012173	0.49889
03-12-2009	COMCAST CORPORATION	-0.0003593	0.83042
12-02-2013	COMCAST CORPORATION	0.000194	0.46283
06-03-2014	COMCAST CORPORATION	0.0012019	0.50348
02-07-2007	CONSOLIDATED COMMUNICATIONS	0.0003858	1.10368
30-06-2014	CONSOLIDATED COMMUNICATIONS	0.0004828	0.86203
05-12-2016	CONSOLIDATED COMMUNICATIONS	0.0008245	0.99978
04-11-2004	CROWN CASTLE INTERNATIONAL	0.0006903	0.84062
08-05-2006	CROWN CASTLE INTERNATIONAL	0.0023984	0.17232
06-10-2006	CROWN CASTLE INTERNATIONAL	0.0021609	0.49794
30-07-2010	CROWN CASTLE INTERNATIONAL	0.0003954	0.75548
16-12-2011	CROWN CASTLE INTERNATIONAL	0.0007004	0.62604
08-04-2016	CROWN CASTLE INTERNATIONAL	0.0003015	0.58601
06-08-1999	DEUTSCHE TELEKOM AG	0.0001454	1.01206
25-05-2000	DEUTSCHE TELEKOM AG	-0.0005564	1.66597
29-06-2001	DEUTSCHE TELEKOM AG	-0.0012483	1.59787
11-01-2002	DEUTSCHE TELEKOM AG	-0.0012958	0.98277
12-11-2003	DEUTSCHE TELEKOM AG	-0.0001348	0.68208
11-10-2004	DEUTSCHE TELEKOM AG	0.0003352	0.92292
05-09-2006	DEUTSCHE TELEKOM AG	-0.0010081	0.58309
10-02-2014	DEUTSCHE TELEKOM AG	0.0013491	1.01299
19-05-2015	DEUTSCHE TELEKOM AG	0.00092	0.9391
29-03-2001	DUN & BRADSTREET CORPORATION	0.004865	0.52281
13-08-2002	DUN & BRADSTREET CORPORATION	0.0002041	0.48464
06-08-2003	ECKOH TECHNOLOGIES PLC	-0.0003955	0.2063
05-02-2007	ECOTEL COMMUNICATION AG	-0.0001472	0.03729
11-09-2007	EUTELSAT COMMUNICATIONS SA	0.0004835	0.6347
31-07-2013	EUTELSAT COMMUNICATIONS SA	-0.0012203	0.47477
12-07-2000	FRONTIER COMMUNICATIONS	0.0019573	0.5754
16-05-2002	FRONTIER COMMUNICATIONS	0.0000467	1.1898
18-09-2006	FRONTIER COMMUNICATIONS	-0.0002076	0.73677
05-07-2007	FRONTIER COMMUNICATIONS	0.0001079	0.75976
13-05-2009	FRONTIER COMMUNICATIONS	-0.000456	1.30892
05-02-2015	FRONTIER COMMUNICATIONS	0.0004395	1.06005

Date	Company	Alpha	Beta
09-05-2013	GLOBAL EAGLE ENTERTAINMENT	-0.000091	0.1145
21-10-2013	GLOBAL EAGLE ENTERTAINMENT	-0.0009138	0.4417
09-05-2016	GLOBAL EAGLE ENTERTAINMENT	-0.0030926	1.19013
05-09-2013	HAWAIIAN TELCOM HOLDCO INC.	0.0013651	0.52536
11-11-2010	HC2 HOLDINGS INC.	0.0030543	0.17345
13-05-2014	HC2 HOLDINGS INC.	0.0010205	0.08879
13-12-2005	IDT CORPORATION	-0.000855	0.58757
26-08-2008	ILIAD SA	0.0016161	0.62547
23-11-2009	INMARSAT PLC	0.0009167	0.63689
17-12-2013	INMARSAT PLC	0.0008516	0.85763
01-06-2010	INTERNET INITIATIVE JAPAN INC.	0.0017045	0.72987
14-02-2006	JAPAN COMMUNICATIONS INC.	-0.0043187	1.26276
06-10-2006	JUBII EUROPE	-0.0011002	0.60458
13-10-2005	KDDI CORPORATION	0.0008263	0.81798
29-09-2006	KDDI CORPORATION	0.0016984	0.74886
24-04-2007	KDDI CORPORATION	0.0014647	0.75737
25-01-2008	KDDI CORPORATION	0.0003965	0.44847
15-12-2010	KDDI CORPORATION	0.0008192	0.60559
10-06-2011	KDDI CORPORATION	0.0016925	0.84122
06-10-2016	KDDI CORPORATION	0.0003922	0.73308
29-09-2006	KCOM	-0.001401	0.42529
14-02-2000	KONINKLIJKE KPN NV	0.0065189	1.90854
30-10-2000	KONINKLIJKE KPN NV	-0.0068134	2.63463
30-01-2002	KONINKLIJKE KPN NV	0.0045413	1.73134
18-10-2004	KONINKLIJKE KPN NV	0.0000361	0.59247
28-06-2005	KONINKLIJKE KPN NV	-0.0008236	0.78364
02-12-2005	KONINKLIJKE KPN NV	0.0007262	0.98726
26-03-2008	KONINKLIJKE KPN NV	0.0005591	0.49566
23-11-2009	KONINKLIJKE KPN NV	0.0015198	0.19528
18-11-2014	KONINKLIJKE KPN NV	-0.000391	1.03551
05-02-2013	LIBERTY GLOBAL PLC	0.0017689	0.64369
16-11-2015	LIBERTY GLOBAL PLC	-0.0003816	1.01539
24-03-2004	LICT	0.0026197	-0.1627
17-06-2013	MITEL NETWORKS CORPORATION	0.0014584	0.16984
11-11-2013	MITEL NETWORKS CORPORATION	0.004075	0.38007
27-04-2015	MITEL NETWORKS CORPORATION	0.0006403	0.43612
15-07-2010	NIPPON TELEGRAPH & TELEPHONE	0.0001653	0.33235
17-06-2013	NIPPON TELEGRAPH & TELEPHONE	0.0010112	0.5369
05-11-2004	NTT DOCOMO INC.	-0.0005121	1.05227
21-12-2007	NTT DOCOMO INC.	0.0002111	0.74712
06-04-2009	NTT DOCOMO INC.	-0.000077	0.47572
02-08-2010	NTT DOCOMO INC.	0.0002245	0.35363
30-01-2012	NTT DOCOMO INC.	-0.0000396	0.32043
30-01-2013	NTT DOCOMO INC.	-0.0006471	0.44108
25-10-2013	NTT DOCOMO INC.	-0.0002485	0.4575
24-07-1998	ORANGE SA	0.0008369	1.18282
26-01-2000	ORANGE SA	0.0025407	1.52319
08-11-2000	ORANGE SA	-0.0019444	2.26475
06-06-2002	ORANGE SA	-0.0043279	1.85276

Date	Company	Alpha	Beta
01-09-2003	ORANGE SA	0.0008698	0.9506
10-02-2005	ORANGE SA	0.0006507	1.26445
28-07-2006	ORANGE SA	-0.0011594	0.78142
16-11-2007	ORANGE SA	0.0015645	0.84697
29-04-2009	ORANGE SA	-0.0009136	0.4938
30-09-2010	ORANGE SA	-0.0003939	0.62699
20-10-2011	ORANGE SA	-0.0000995	0.77244
27-11-2012	ORANGE SA	-0.0025777	1.00231
31-03-2014	ORANGE SA	0.0010573	1.05856
15-09-2014	ORANGE SA	0.0006229	1.18813
23-02-2015	ORANGE SA	0.0018974	1.11641
08-02-2016	ORANGE SA	0.0019006	1.06662
23-02-2011	ORBCOMM INC.	0.0029368	-0.0179
16-01-2015	ORBCOMM INC.	-0.0006892	1.01666
11-01-2000	PEGASUS COMMUNICATIONS	0.0061075	0.22762
15-12-2005	PROXIMUS SA	-0.0001692	0.58509
25-08-2006	PROXIMUS SA	-0.0001138	0.32173
15-02-2008	PROXIMUS SA	0.0015992	0.43107
15-04-2011	PROXIMUS SA	-0.0004189	0.5969
03-10-2012	QUEBECOR INC.	-0.0011999	0.2869
01-09-2000	ROGERS COMMUNICATIONS INC.	-0.0021086	0.62964
09-07-2001	ROGERS COMMUNICATIONS INC.	-0.0001041	0.52499
13-09-2004	ROGERS COMMUNICATIONS INC.	-0.0004281	0.90558
11-05-2005	ROGERS COMMUNICATIONS INC.	0.0019506	-0.0278
05-10-2010	ROGERS COMMUNICATIONS INC.	0.0009668	0.38736
14-01-2013	ROGERS COMMUNICATIONS INC.	0.0013217	0.18204
23-09-2013	ROGERS COMMUNICATIONS INC.	-0.0011498	0.39341
23-10-2014	ROGERS COMMUNICATIONS INC.	-0.0003086	0.37252
24-06-2015	ROGERS COMMUNICATIONS INC.	-0.0006221	0.33824
17-03-2006	SBA COMMUNICATIONS	0.0019436	0.80188
21-02-2012	SBA COMMUNICATIONS	0.0013735	0.60656
01-11-2000	SHAW COMMUNICATIONS INC.	-0.0000914	0.45548
08-09-2003	SHAW COMMUNICATIONS INC.	0.0003142	1.29655
16-07-2009	SHAW COMMUNICATIONS INC.	-0.0011141	0.5973
12-02-2010	SHAW COMMUNICATIONS INC.	0.000188	0.34872
14-01-2013	SHAW COMMUNICATIONS INC.	0.0009663	0.29875
31-07-2014	SHAW COMMUNICATIONS INC.	0.0005524	0.42454
16-12-2015	SHAW COMMUNICATIONS INC.	0.0001897	0.47521
30-08-2004	SHENANDOAH TELECOM	0.0012294	1.3779
10-08-2015	SHENANDOAH TELECOM	0.0004861	1.03851
13-02-2008	SKY PERFECT JSAT CORPORATION	-0.0007723	0.94137
27-05-2004	SOFTBANK TECHONOLOGY	-0.0010028	2.00884
26-10-2004	SOFTBANK TECHONOLOGY	0.0001682	1.35044
17-03-2006	SOFTBANK TECHONOLOGY	-0.0022261	0.98757
12-03-2012	SOFTBANK TECHONOLOGY	0.0018739	0.45641
01-10-2012	SOFTBANK TECHONOLOGY	-0.0022778	1.01083
18-10-2013	SOFTBANK TECHONOLOGY	0.0043742	0.6505
06-08-2014	SOFTBANK TECHONOLOGY	0.0005325	1.09785
18-07-2016	SOFTBANK GROUP CORPORATION	0.0011844	1.09695

Date	Company	Alpha	Beta
02-03-2009	M3 INC.	0.0019656	0.5274
03-03-2011	SPOK	-0.0022053	1.57866
09-07-1999	SWISSCOM AG	0.0004302	0.80051
19-01-2001	SWISSCOM AG	-0.0018039	1.2711
12-07-2001	SWISSCOM AG	0.0013647	0.84585
19-12-2006	SWISSCOM AG	0.0001931	0.48199
17-06-2014	SWISSCOM AG	0.0009182	0.55547
03-10-2000	TELE2 AB	-0.0023017	0.93972
14-11-2001	TELE2 AB	0.000552	1.2441
17-02-2003	TELE2 AB	0.0028317	1.08769
14-10-2004	TELE2 AB	-0.0019076	1.0458
15-07-2005	TELE2 AB	-0.0019073	1.11083
30-06-2006	TELE2 AB	-0.000913	0.88227
01-06-2007	TELE2 AB	0.000928	1.10748
13-07-2009	TELE2 AB	-0.0002251	0.83793
14-12-2009	TELE2 AB	0.0021195	0.76288
04-11-2015	TELE2 AB	-0.001348	0.85317
21-06-2016	TELE2 AB	-0.0007495	0.93267
18-09-2006	TELECOM ITALIA SPA	-0.0005413	1.00496
23-07-2013	TELEFONICA DEUTSCHLAND HOLDING	-0.0009794	0.41629
29-11-2006	TELENET GROUP HOLDING NV	0.0006253	0.57662
10-06-2008	TELENET GROUP HOLDING NV	-0.0010863	0.46488
20-04-2015	TELENET GROUP HOLDING NV	0.0000134	0.80388
27-11-2000	TELEPHONE AND DATA SYSTEMS INC.	-0.0005366	1.57555
28-06-2011	TELEPHONE AND DATA SYSTEMS INC.	-0.0015734	0.88979
11-06-2012	TELEPHONE AND DATA SYSTEMS INC.	-0.0013423	1.103
26-02-2013	TELEPHONE AND DATA SYSTEMS INC.	-0.0005442	1.48133
08-10-2013	TELEPHONE AND DATA SYSTEMS INC.	0.002319	0.96373
01-05-2014	TELEPHONE AND DATA SYSTEMS INC.	-0.0010877	0.74851
26-06-2001	TELIA COMPANY AB	0.0019199	0.88723
26-03-2002	TELIA COMPANY AB	-0.001864	1.01716
09-07-2004	TELIA COMPANY AB	-0.0018154	0.7659
28-03-2005	TELIA COMPANY AB	0.0001551	1.00255
09-02-2006	TELIA COMPANY AB	0.0003966	0.74121
16-11-2006	TELIA COMPANY AB	0.0005425	0.74694
17-06-2008	TELIA COMPANY AB	0.0004727	0.64063
02-02-2010	TELIA COMPANY AB	0.0001416	0.77025
06-12-2010	TELIA COMPANY AB	0.0005791	0.61254
07-07-2014	TELIA COMPANY AB	-0.000872	0.8935
07-11-2016	TELIA COMPANY AB	-0.0008086	0.86942
21-08-2000	TELUS CORPORATION	0.0015168	0.33806
10-05-2001	TELUS CORPORATION	-0.0007469	0.32268
16-11-2004	TELUS CORPORATION	0.0018246	0.4727
08-09-2009	TELUS CORPORATION	-0.0011631	0.46104
23-10-2013	TELUS CORPORATION	-0.0001161	0.21465
24-04-2003	TISCALI SPA	0.0002381	1.62828
17-10-2012	UNITED INC	-0.0003678	0.67773
16-03-2005	UNITED INTERNET AG	0.001136	1.3539
09-05-2006	UNITED INTERNET AG	0.0026518	1.35336
12-12-2008	UNITED INTERNET AG	-0.0037147	0.82285
03-09-2014	UNITED INTERNET AG	0.0002306	1.47296
15-12-2016	UNITED INTERNET AG	-0.0010731	1.12649
10-05-2002	UNITED STATES CELLULAR CORPORAT	-0.0008506	1.15873
02-05-2005	VERIZON COMMUNICATIONS INC.	-0.0012677	0.89907
27-01-2011	VERIZON COMMUNICATIONS INC.	0.0011742	0.79726
01-06-2012	VERIZON COMMUNICATIONS INC.	0.0010611	0.77627
02-09-2013	VERIZON COMMUNICATIONS INC.	-0.0000386	1.07215
21-01-2014	VERIZON COMMUNICATIONS INC.	-0.0015022	1.33219
12-05-2015	VERIZON COMMUNICATIONS INC.	-0.0001578	0.90402
22-02-2016	VERIZON COMMUNICATIONS INC.	0.001064	0.91711
25-07-2016	VERIZON COMMUNICATIONS INC.	0.0011484	0.59344
01-04-1998	VIVENDI SA	0.0018455	0.51913
21-05-2001	VIVENDI SA	0.0001154	0.97511
30-09-2002	VIVENDI SA	-0.0003285	1.92641
05-01-2005	VIVENDI SA	0.0000334	1.14633
16-12-2005	VIVENDI SA	-0.0008593	1.09138
25-10-2007	VIVENDI SA	-0.0003469	0.73179
04-04-2011	VIVENDI SA	-0.0004372	0.98488
05-09-2011	VIVENDI SA	-0.0001096	0.9282
28-10-2013	VIVENDI SA	0.0004554	0.80462
28-03-2014	VIVENDI SA	0.0008919	0.95417
19-05-2016	VIVENDI SA	-0.0007614	0.79762
18-01-1999	VODAFONE GROUP PLC	0.0023767	1.33633
01-05-2002	VODAFONE GROUP PLC	-0.003295	1.8605
05-08-2003	VODAFONE GROUP PLC	-0.0008325	1.03082
03-06-2004	VODAFONE GROUP PLC	-0.0005248	1.51189
15-11-2005	VODAFONE GROUP PLC	-0.0000424	0.90151
11-07-2006	VODAFONE GROUP PLC	-0.000759	1.09318
12-02-2007	VODAFONE GROUP PLC	0.0012493	1.15593
06-11-2008	VODAFONE GROUP PLC	0.0006509	0.97075
04-02-2010	VODAFONE GROUP PLC	0.0003712	0.59229
29-05-2007	WINDSTREAM CORPORATION	0.0003025	0.77001
11-05-2009	WINDSTREAM CORPORATION	0.0011775	0.98546
17-08-2010	WINDSTREAM CORPORATION	0.0007019	0.72916
01-08-2011	WINDSTREAM CORPORATION	-0.0002019	0.46151
01-04-2016	ZAYO GROUP HOLDINGS INC.	-0.001028	0.73776
07-11-2016	ZAYO GROUP HOLDINGS INC.	0.0011624	0.69709

Appendix 6: *R-code for estimating the market model coefficients in the CAR[-1,1] window. The complete set for R-codes used in this thesis can be found on the USB*

```
for (i in 1:283){
  info <- as.character(request[c("FirmID", "Date", "MarketID")][i,])
  f_lookup <- which(firm$FirmID == info[1] & firm$Date == info[2])
  if (length(f_lookup) == 0){
    er_1[i] <- info
  } else {
    f_est_start[i] <- f_lookup-131
    f_est_end[i] <- f_lookup-2
  }

  m_lookup <- which(market$MarketID == info[3] & market$Date == info[2])

  if (length(m_lookup) == 0){
    er_2[i] <- info
  } else {
    m_est_start[i] <- m_lookup-131
    m_est_end[i] <- m_lookup-2
  }
  df[[i]] <- data.frame(mreturn = market$Return[m_est_start[i]:m_est_end[i]],
                        freturn = firm$Return[f_est_start[i]:f_est_end[i]])
  lm1[[i]] <- lm(freturn ~ mreturn, data = df[[i]])
  lm_summary[[i]] <- summary(lm1[[i]])
  print(i)
}
```

Appendix 7: *Parametric and Non-Parametric tests for AR and CAR in Total Sample*

TOTAL SAMPLE (N=283)					
Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-10	0.0011	0.0011	4.2112***	0.919	0.0594
-9	0.0003	0.0014	1.2003	1.1809	-1.1294
-8	-0.0004	0.0009	-1.6529	0.8202	-0.2972
-7	0.0006	0.0015	2.2324**	1.3074	-1.2483
-6	0.0008	0.0023	3.1173***	1.9876**	-2.1994**
-5	0.0006	0.0029	2.4989**	2.5329**	2.1994**
-4	0.0008	0.0037	3.0189***	3.1917***	1.8428*
-3	0.0003	0.0040	1.2743	3.4698***	-1.0105
-2	0.0004	0.0044	1.5364	3.805***	-1.3672
-1	-0.0004	0.0040	-1.5412	3.4687***	0.535
0	-0.0004	0.0035	-1.7821	3.0798***	0.2972
1	-0.0030	0.0005	-12.0954***	0.4404	-2.675***
2	0.0003	0.0008	1.3557	0.7363	-0.4161
3	0.0000	0.0009	0.1371	0.7662	-1.0105
4	-0.0005	0.0004	-1.9044*	0.3506	-1.3672
5	-0.0002	0.0002	-0.9259	0.1485	-2.0805**
6	0.0005	0.0006	1.8809*	0.559	-0.6539
7	-0.0005	0.0001	-2.1018**	0.1003	-2.5561**
8	-0.0018	-0.0016	-6.9852***	-1.424	-3.0316***
9	-0.0007	-0.0023	-2.7518***	-2.0245**	-0.7728
10	0.0004	-0.0019	1.5931	-1.6768*	0.535
Std.dev	0.0003	0.0012			

Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-5	0.0006	0.0006	2.8659***	0.8641	1.9616**
-4	0.0007	0.0013	3.757***	1.9969**	1.7239*
-3	0.0003	0.0016	1.4461	2.4329**	-0.8917
-2	0.0004	0.0020	1.8004*	2.9757***	-1.1294
-1	-0.0004	0.0016	-2.0289**	2.364**	0.535
0	-0.0005	0.0011	-2.3068**	1.6685*	0.1783
1	-0.0030	-0.0019	-15.3115***	-2.9481***	-2.4372**
2	0.0003	-0.0017	1.4514	-2.5105**	-0.535
3	0.0000	-0.0016	0.0279	-2.5021**	-0.8917
4	-0.0005	-0.0021	-2.5127**	-3.2597***	-1.4861
5	-0.0002	-0.0023	-1.0181	-3.5667***	-2.0805**
Std.dev	0.0002	0.0007			

Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-1	-0.0004	-0.0004	-2.2402**	-1.2934	0.2972
0	-0.0005	-0.0009	-2.5386**	-2.759***	0.1783
1	-0.0030	-0.0039	-16.4176***	-12.2377***	-2.675***
Std.dev	0.0002	0.0003			

Appendix 8: *Parametric and Non-Parametric tests for AR and CAR in North America*

NORTH AMERICA (N=133)					
Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-10	-0.0001	-0.0001	-0.1398	-0.0305	-0.4336
-9	-0.0003	-0.0004	-0.411	-0.1202	-1.4741
-8	-0.0017	-0.0021	-2.1589**	-0.5913	-0.2601
-7	-0.0015	-0.0036	-1.9082*	-1.0077	-1.9944**
-6	-0.0010	-0.0046	-1.2966	-1.2906	-1.6475*
-5	0.0002	-0.0043	0.323	-1.2202	1.4741
-4	-0.0003	-0.0046	-0.4209	-1.312	0.7804
-3	-0.0001	-0.0047	-0.1107	-1.3362	-0.607
-2	0.0018	-0.0030	2.2967**	-0.835	-0.2601
-1	0.0002	-0.0028	0.238	-0.783	0.4336
0	-0.0019	-0.0047	-2.4528**	-1.3183	0.0867
1	-0.0071	-0.0117	-9.1341***	-3.3115***	-3.7286***
2	-0.0009	-0.0126	-1.1304	-3.5582***	0.4336
3	-0.0007	-0.0133	-0.8665	-3.7473***	-0.7804
4	0.0009	-0.0123	1.1986	-3.4857***	-0.7804
5	-0.0003	-0.0127	-0.449	-3.5837***	-1.9944**
6	0.0007	-0.0120	0.8968	-3.388***	-0.7804
7	-0.0026	-0.0146	-3.4097***	-4.132***	-1.9944**
8	-0.0020	-0.0166	-2.5599**	-4.6906***	-2.5146**
9	-0.0007	-0.0173	-0.9383	-4.8954***	-0.607
10	0.0012	-0.0162	1.4914	-4.5699***	0.7804
Std.dev	0.000771912	0.0035			

Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-5	0.0002	0.0002	0.372	0.1122	1.4741
-4	-0.0003	-0.0001	-0.4848	-0.034	0.7804
-3	-0.0001	-0.0002	-0.1275	-0.0724	-0.607
-2	0.0018	0.0016	2.6454***	0.7252	-0.2601
-1	0.0002	0.0018	0.2742	0.8079	0.4336
0	-0.0019	-0.0001	-2.8252***	-0.044	0.0867
1	-0.0071	-0.0071	-10.5209***	-3.2162***	-3.7286***
2	-0.0009	-0.0080	-1.302	-3.6087***	0.4336
3	-0.0007	-0.0087	-0.9981	-3.9097***	-0.7804
4	0.0009	-0.0078	1.3806	-3.4934***	-0.7804
5	-0.0003	-0.0081	-0.5172	-3.6493***	-1.9944**
Std.dev	0.000670161	0.0022			

Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-1	0.0002	0.0002	0.288	0.1663	0.4336
0	-0.0019	-0.0017	-2.9674***	-1.547	0.0867
1	-0.0071	-0.0088	-11.0504***	-7.9269***	-3.7286***
Std.dev	0.00063805	0.0011			

Appendix 9: *Parametric and Non-Parametric tests for AR and CAR in Europe*

EUROPE (N=121)					
Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-10	0.0028	0.0028	4.4579***	0.9728	0.4545
-9	0.0017	0.0045	2.7263***	1.5677	-0.4545
-8	0.0002	0.0047	0.3486	1.6438	-0.0909
-7	0.0011	0.0058	1.7516*	2.026**	0.2727
-6	0.0023	0.0081	3.6889***	2.831***	-1.1818
-5	0.0029	0.0110	4.6309***	3.8415***	1.1818
-4	0.0034	0.0143	5.4484***	5.0305***	2.2727**
-3	0.0018	0.0162	2.9412***	5.6723***	-0.8182
-2	-0.0003	0.0159	-0.4421	5.5758***	-2.0909**
-1	-0.0002	0.0157	-0.3335	5.503***	0.4545
0	0.0008	0.0165	1.2894	5.7844***	0.4545
1	0.0011	0.0176	1.8075*	6.1788***	0.6364
2	0.0006	0.0182	1.0114	6.3996***	-0.8182
3	-0.0002	0.0181	-0.309	6.3321***	-0.8182
4	-0.0013	0.0168	-2.0153**	5.8924***	-1.5455
5	-0.0008	0.0160	-1.2412	5.6215***	-0.6364
6	0.0003	0.0163	0.4986	5.7303***	0.2727
7	0.0003	0.0166	0.4355	5.8254***	-2.2727**
8	-0.0003	0.0163	-0.4863	5.7193***	-1.7273*
9	-0.0010	0.0153	-1.5664	5.3774***	-0.8182
10	0.0001	0.0154	0.1762	5.4159***	1
Std.dev	0.000622073	0.0029			

Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-5	0.004	0.0035	6.8527***	2.0662**	1.1818
-4	0.003	0.0068	6.2829***	3.9605***	2.2727**
-3	0.000	0.0072	0.8081	4.2042***	-0.8182
-2	-0.001	0.0062	-1.8741*	3.6391***	-2.0909**
-1	0.001	0.0068	1.0699	3.9617***	0.4545
0	0.001	0.0078	2.0388**	4.5765***	0.4545
1	0.001	0.0090	2.319**	5.2757***	0.6364
2	0.000	0.0091	0.1194	5.3117***	-0.8182
3	0.000	0.0086	-0.8643	5.0511***	-0.8182
4	-0.002	0.0066	-3.9944***	3.8467***	-1.5455
5	0.001	0.0071	1.0021	4.1488***	-0.6364
Std.dev	0.001	0.0017			

Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-1	0.0006	0.0006	3.5715***	2.062**	0.4545
0	0.0011	0.0016	6.8057***	5.9913***	0.4545
1	0.0012	0.0028	7.7412***	10.4607***	0.6364
Std.dev	0.000154591	0.0003			

Appendix 10: *Parametric and Non-Parametric tests for AR and CAR in Japan*

JAPAN (N=29)					
Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-10	-0.0007	-0.0007	-0.199	-0.0434	0.1857
-9	0.0018	0.0011	0.4886	0.0632	0.5571
-8	0.0044	0.0054	1.1706	0.3186	-0.1857
-7	0.0024	0.0078	0.6363	0.4575	-0.1857
-6	0.0030	0.0108	0.7939	0.6307	-0.9285
-5	-0.0098	0.0010	-2.623***	0.0583	1.2999
-4	-0.0046	-0.0036	-1.2434	-0.213	-0.5571
-3	0.0018	-0.0019	0.4779	-0.1087	-0.1857
-2	-0.0003	-0.0022	-0.0873	-0.1278	0.5571
-1	-0.0069	-0.0091	-1.861*	-0.5339	-0.1857
0	-0.0001	-0.0092	-0.0215	-0.5385	-0.1857
1	-0.0023	-0.0115	-0.6287	-0.6757	-1.6713*
2	0.0071	-0.0045	1.8994*	-0.2613	-0.5571
3	0.0053	0.0008	1.4141	0.0473	0.1857
4	-0.0003	0.0005	-0.085	0.0288	0.5571
5	-0.0028	-0.0023	-0.7629	-0.1377	-0.9285
6	0.0010	-0.0013	0.2714	-0.0785	-0.9285
7	0.0051	0.0037	1.3651	0.2194	0.9285
8	-0.0037	0.0000	-1.0007	0.0011	-0.5571
9	0.0003	0.0004	0.0929	0.0213	0.5571
10	-0.0061	-0.0057	-1.6282	-0.334	-2.0426**
Std.dev	0.003723144	0.0171			

Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-5	-0.0098	-0.0098	-3.1503***	-0.9499	1.2999
-4	-0.0046	-0.0144	-1.4933	-1.4001	-0.5571
-3	0.0018	-0.0126	0.5739	-1.2271	-0.1857
-2	-0.0003	-0.0129	-0.1049	-1.2587	0.5571
-1	-0.0069	-0.0199	-2.2351**	-1.9326*	-0.1857
0	-0.0001	-0.0199	-0.0258	-1.9404*	-0.1857
1	-0.0023	-0.0223	-0.7551	-2.168**	-1.6713*
2	0.0071	-0.0152	2.2812**	-1.4802	-0.5571
3	0.0053	-0.0100	1.6984*	-0.9681	0.1857
4	-0.0003	-0.0103	-0.102	-0.9989	0.5571
5	-0.0028	-0.0131	-0.9163	-1.2752	-0.9285
Std.dev	0.003099947	0.0103			

Days in event window	AR	CAR	Parametric		Non-Parametric
			AR = 0	CAR = 0	Sign test, AR
-1	-0.0069	-0.0069	-4.9225***	-2.842***	-0.1857
0	-0.0001	-0.0070	-0.0568	-2.8748***	-0.1857
1	-0.0023	-0.0093	-1.6629*	-3.8349***	-1.6713*
Std.dev	0.001407531	0.0024			

***Appendix 11**: Complete OLS- output from the Total Sample*

	Dependent variable:		
	CAR1	CAR5	CAR10
	(1)	(2)	(3)
LIQ	-0.018*		
	(0.011)		
Q		0.0003	0.0004
		(0.0002)	(0.0003)
ROE.trend		0.001**	
		(0.0005)	
Sales.ratio	0.017**	0.045***	0.065***
	(0.008)	(0.017)	(0.019)
Cost.eff.		-0.033	-0.030
		(0.030)	(0.039)
Growth.assets		0.012*	0.012
		(0.007)	(0.009)
Equity.Assets	-0.029*	-0.064**	-0.066*
	(0.015)	(0.029)	(0.039)
R.Unrelated1	-0.002	0.012	0.005
	(0.007)	(0.011)	(0.013)
Payment1	-0.012	-0.006	-0.013
	(0.011)	(0.018)	(0.020)
Payment2	0.002	-0.005	0.002
	(0.007)	(0.010)	(0.013)
Dom.CB1	-0.012		-0.002
	(0.007)		(0.017)
Prior.Own1	0.011*	0.018	0.023
	(0.006)	(0.011)	(0.015)
GDP		0.008***	0.009**
		(0.002)	(0.004)
Constant	0.006	-0.007	-0.023
	(0.010)	(0.030)	(0.037)
Observations	283	283	283
R^2	0.069	0.137	0.127
Adjusted R^2	0.042	0.102	0.091
Residual Std. Error	0.051 (df = 274)	0.080 (df = 271)	0.099 (df = 271)
F Statistic	2.529** (df = 8; 274)	3.913*** (df = 11; 271)	3.573*** (df = 11; 271)
Note:			*p<0.1; **p<0.05; ***p<0.01

***Appendix 12**: Complete OLS- output from North America*

	Dependent variable:		
	CAR1	CAR5	CAR10
	(1)	(2)	(3)
Q	0.036**	0.034*	0.040
	(0.014)	(0.020)	(0.025)
ROE.trend	0.001***	0.002**	
	(0.0003)	(0.001)	
Sales.ratio	-0.023		
	(0.017)		
LIQ			-0.035*
			(0.021)
ROA.trend			0.005***
			(0.002)
Cost.eff.		-0.122*	-0.153**
		(0.068)	(0.071)
Growth.assets		0.033**	0.043***
		(0.015)	(0.016)
Equity.Assets		-0.060	-0.067
		(0.041)	(0.041)
R.Unrelated1	0.008	0.023	0.015
	(0.011)	(0.018)	(0.019)
Payment1	-0.003	0.023	0.034
	(0.018)	(0.025)	(0.027)
Payment2	0.002	0.013	0.013
	(0.010)	(0.016)	(0.017)
Dom.CB1	-0.051	-0.053	-0.074*
	(0.034)	(0.038)	(0.045)
Prior.Own1	0.019**	0.033	0.007
	(0.010)	(0.023)	(0.022)
GDP			0.008
			(0.006)
Constant	-0.029*	0.062	0.078
	(0.015)	(0.063)	(0.068)
Observations	133	133	133
R^2	0.170	0.276	0.319
Adjusted R^2	0.116	0.217	0.251
Residual Std. Error	0.056 (df = 124)	0.084 (df = 122)	0.092 (df = 120)
F Statistic	3.173*** (df = 8; 124)	4.653*** (df = 10; 122)	4.685*** (df = 12; 120)

***Appendix 13**: Complete OLS- output from Europe*

	Dependent variable:		
	CAR1	CAR5	CAR10
	(1)	(2)	(3)
LIQ	-0.027*		
	(0.014)		
ROA.trend			-0.004***
			(0.001)
Sales.ratio	0.035***	0.078***	0.100***
	(0.012)	(0.012)	(0.017)
Cost.eff.	0.013**		0.041***
	(0.006)		(0.014)
Equity.Assets	-0.028*		
	(0.016)		
Sales.trend		0.025**	
		(0.012)	
R.Unrelated1	0.0002	0.013	0.001
	(0.008)	(0.013)	(0.019)
Payment1	-0.037***	-0.032	-0.064**
	(0.014)	(0.020)	(0.030)
Payment2	0.005	-0.006	0.004
	(0.007)	(0.013)	(0.016)
Dom.CB1	0.002	0.002	-0.010
	(0.007)	(0.011)	(0.017)
Prior.Own1	0.007	0.004	0.019
	(0.006)	(0.010)	(0.016)
Interest	-0.004		
	(0.003)		
GDP		0.005**	
		(0.002)	
M.A.Wave			0.037***
			(0.013)
Constant	-0.002	-0.080***	-0.130***
	(0.016)	(0.017)	(0.026)
Observations	121	121	121
R^2	0.265	0.301	0.309
Adjusted R^2	0.198	0.251	0.253
Residual Std. Error	0.037 (df = 110)	0.057 (df = 112)	0.080 (df = 111)
F Statistic	3.969*** (df = 10; 110)	6.030*** (df = 8; 112)	5.504*** (df = 9; 111)

***Appendix 14**: Complete OLS- output from Japan*

	Dependent variable:		
	CAR1	CAR5	CAR10
	(1)	(2)	(3)
LN.EV	-0.018***		
	(0.005)		
Q		0.004	-0.046***
		(0.016)	(0.013)
LIQ		0.395**	0.334*
		(0.167)	(0.182)
ROE.trend	0.151**	0.031	
	(0.068)	(0.076)	
ROA.trend	-0.179**	-0.075	
	(0.070)	(0.079)	
Sales.trend	0.252**		
	(0.111)		
Sales.ratio		0.197**	0.203***
		(0.082)	(0.062)
Cost.eff.		-0.114	
		(0.240)	
Growth.assets	-0.119***	-0.018	
	(0.045)	(0.073)	
M.A.Exp.	-0.038*		
	(0.021)		
R.Unrelated1	-0.002	0.057	0.012
	(0.014)	(0.062)	(0.046)
Payment1	0.006	-0.024	-0.081
	(0.026)	(0.059)	(0.054)
Payment2	-0.008	-0.032	-0.012
	(0.018)	(0.028)	(0.028)
Dom.CB1	-0.074***	-0.014	-0.024
	(0.023)	(0.038)	(0.031)
Prior.Own1	-0.027	-0.036	-0.039
	(0.019)	(0.037)	(0.037)
GDP	0.012***	0.018***	0.019***
	(0.003)	(0.007)	(0.006)
Interest		0.039	
		(0.040)	
M.A.Wave		0.059	
		(0.096)	
Constant	0.183	-0.259	-0.251***
	(0.117)	(0.254)	(0.090)
Observations	29	29	29
R^2	0.690	0.668	0.665
Adjusted R^2	0.457	0.284	0.506
Residual Std. Error	0.043 (df = 16)	0.081 (df = 13)	0.090 (df = 19)
F Statistic	2.965** (df = 12; 16)	1.741 (df = 15; 13)	4.190*** (df = 9; 19)
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix 15: *Kruskali-Wallis Output*

```
> kruskal.test(CAR1 ~ EURO.NA.JP, data = analyse)

        Kruskal-Wallis rank sum test

data:  CAR1 by EURO.NA.JP
Kruskal-Wallis chi-squared = 4.5969, df = 2, p-value = 0.1004

> kruskal.test(CAR5 ~ EURO.NA.JP, data = analyse)

        Kruskal-Wallis rank sum test

data:  CAR5 by EURO.NA.JP
Kruskal-Wallis chi-squared = 1.159, df = 2, p-value = 0.5602

> kruskal.test(CAR10 ~ EURO.NA.JP, data = analyse)

        Kruskal-Wallis rank sum test

data:  CAR10 by EURO.NA.JP
Kruskal-Wallis chi-squared = 3.2598, df = 2, p-value = 0.196
```