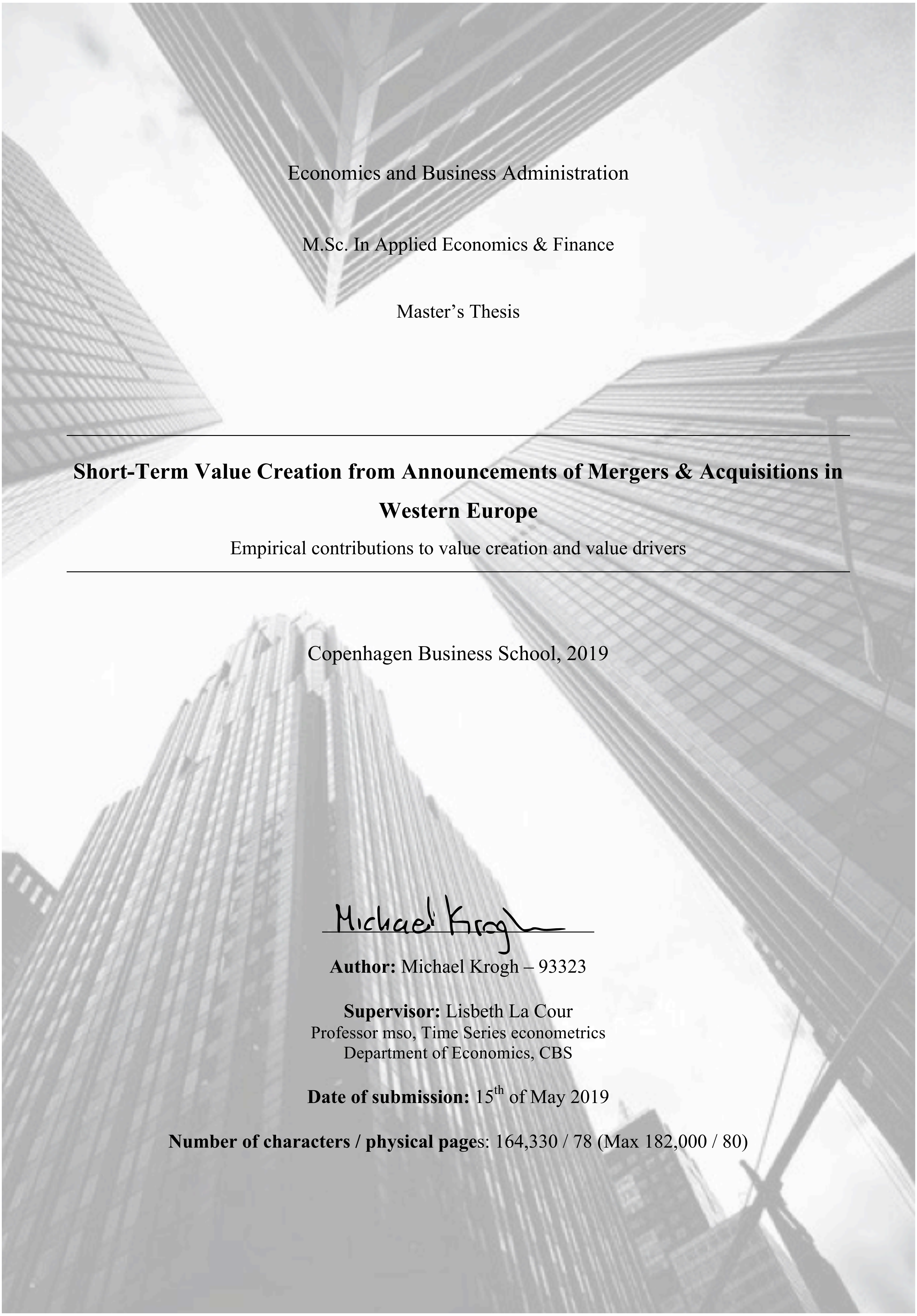


Economics and Business Administration

M.Sc. In Applied Economics & Finance

Master's Thesis

Short-Term Value Creation from Announcements of Mergers & Acquisitions in Western Europe

Empirical contributions to value creation and value drivers

Copenhagen Business School, 2019

Michael Krogh

Author: Michael Krogh – 93323

Supervisor: Lisbeth La Cour
Professor mso, Time Series econometrics
Department of Economics, CBS

Date of submission: 15th of May 2019

Number of characters / physical pages: 164,330 / 78 (Max 182,000 / 80)

Abstract

This thesis researches the value creation from Mergers & Acquisitions, as well as the value drivers in Western Europe between year 2014 and 2018. Mergers & Acquisitions is a popular growth strategy used by many companies to either establish a foothold in new markets, increase their market share in established markets or to acquire new competencies. Although it is a popular strategy, it is also a risky strategy that often do not deliver shareholder returns which justify the high premiums paid.

The value creation is examined by applying an event study methodology to analyze the market reactions to announcements of Mergers & Acquisitions. This is done by calculating and testing the abnormal returns from stock price developments in event windows around the announcement date. To test market efficiency and the sensitivity of abnormal returns, four event windows with different length are constructed. To evaluate and test the transaction specific value drivers, this thesis applies cross-sectional regression. The final dataset includes announcement data from 189 bidders and 142 target across 202 transactions. All bidders and targets are publically traded companies and originate from 18 different countries.

The analysis of abnormal returns shows bidders earn zero abnormal returns in a 21-day event window, while targets on average earn 13.68% abnormal return over the 21-day event window. When testing value drivers, I find both bidders and targets earn higher abnormal returns, when payments are made in cash compared to payment in stocks. Bidders earn 7.1% more and targets 10.2% more in a 21-day event window. This finding is in line with both the signalling theory and the pecking-order theory. Further I find no statistical difference in abnormal returns between cash and mixed payment. Testing for differences in abnormal returns from focused (i.e. intra-industry) and diversifying transactions, I find zero statistical difference. The same result is found when I test the difference between domestic and cross-border transactions. These results suggest Western European capital markets are too efficient and integrated for significant differences to occur. Finally, I test the free cash flow hypothesis, which states cash rich bidders often make value destroying investments. I find this not to be true, as my analysis suggests higher abnormal returns to bidders with higher cash flows, however this finding lack the statistical significance to be conclusive. For targets, I also find evidence of higher value creation to companies with high cash flows, although this result also lack statistical significance to be conclusive.

Table of Contents

1 Introduction

1.1 Motivation

The Western European Mergers & Acquisitions (M&A) market has been thriving the last 5 years (Mergermarket, 2018). Using the market reactions to M&A announcements, this thesis investigates if M&A have been a value creating strategy for companies, and its shareholder. In this thesis, value creation from M&A is defined as positive abnormal returns to shareholders, and it is measured in four event windows with different lengths. Moreover, I extend the study by exploring potential value drivers, that were identified by previous researchers, including the method of payment, underlying strategies and cash flows.

Despite the high activity level in the Western European M&A market in the last 5 years, the short-term value creation from this time-period remains relatively untouched by academia. Martynova & Renneboog (2011) studied European M&As in the fifth merger wave from 1993 to 2001, and Aevoae, Dicu, & Mardiros (2018), looked specifically at cross-border transactions and the flow of foreign direct investments (FDI) in Europe between 2005 and 2016. More recent papers mostly focus on the US market, among them is Alexandridis, Antypas, & Travlos (2017), who studied post-2009 M&As. Thus, leaving a hole in the academic literature. This hole in the literature is the backbone of my motivation for this research.

The investigations of this thesis focus purely on the announcement effect and short-term value creation from M&A. The motivation behind is not to develop strategies for M&A or other investments types for investors to use, but to present empirical evidence on the actual condition of the Western European M&A market and compare these results to those of other markets and time-periods.

This thesis uses the theoretical event study framework of MacKinley (1997) to measure the value creation to bidders and targets. Attention is devoted to the announcement day and the surrounding event windows, while an estimation period is used to calculate the expected normal return using the market model. The extension of testing potential value drivers is carried out using cross-sectional regression, where the dependent variable is the cumulative abnormal return (CAR) for bidders and targets separately.

The empirical tests are conducted on a data sample consisting on completed M&A transactions between 1/1-2014 and 31/12-2018. After considering the methodology and data availability the final sample consists of 189 bidders and 142 targets.

1.2 Research question

The research question is the core of this thesis and works as a guide in the data selection, methodology and empirical analysis. The final goal of this master's thesis is to provide a comprehensive answer to this question. Therefore, the research question should be measurable, relevant and specific. I have formulated the following two-step research question:

Do M&A announcements lead to any abnormal returns to shareholders of the involved parties?

The above research question is followed up by looking at some transaction characteristics that may influence the abnormal returns. Thus, I formulate the second part of the research question:

Are there any specific transaction characteristics that enhance or constrain the abnormal returns to shareholders?

The research question opens to several sub-questions, such as

1) How can value creation be measured, it might differ from shareholders to stakeholders?
2) Does the value creation to target and bidder shareholders differ, and if so, why?
3) What results have been found in previous research, and are such results relevant to this thesis?
4) Which empirical methods ensures reliable results and validity of this thesis?
5) What are the implications of my results, and how do they compare to previous findings?

1.3 Structure

This thesis is divided into four sections. Section one includes the research question, literature review and the theory part, used for hypotheses formulation. Section two covers the methodology and data collection. While section three includes the empirical analyzes, using the data collected and methodology presented in section two. Section four discusses the results and make final conclusions.

1.4 Delimitations

Due to the limit of time and number of pages available for this thesis, I have set up some limitations for my research. These will be discussed in the following paragraphs.

Value creation can be measured in many ways, and it often depends on which stakeholder's point of view is taken. I have decided to look at value creation for shareholders only. Consequently, I use the stock price to measure value creation, because the development in the share price directly affects the wealth of shareholders through capital income. Consequently, I disregard all other effects from M&A activities that impact other stakeholders. This limitation makes value creation quantifiable and specific. Further, this limitation is in line with the agency theory, where corporate managers work as agents, in the best interest, of shareholders to maximize value.

As stock returns are used to measure value creation, I am working under the assumption of efficient markets, where there is no or very limited external noise to manipulate stock prices. Therefore, under the efficient markets assumption stock prices represent the true and fair value of the sample companies and the transactions they participate in. Had value creation been defined in another way, like a DCF valuation based on accounting data, differences in accounting practices and standards would result in incomparable data. This could compromise the validity and reliability of the answer provided for the research question. This is not an unreasonable assumption because stocks an average and over time adhere to it (Bruner, 2002).

The literature review is very specific and narrow by choice. I have only included previous research that is relevant to this thesis and its research question. M&A is topic for a vast and still growing amount of research where value creation is discussed from different perspectives. However, due to a limit on number of pages available I have excluded these. Some readers might wish for a deeper discussion around the value creation in M&A activities, but this is outside the scope of this thesis.

This thesis will be written based on quantitative methodologies such as an event study and cross-sectional regression analysis. This is a common practice used by previous researchers within this topic and in line with the methodology taught throughout the Cand Merc AEF program. I am aware that other methodologies, including qualitative ones, are available and could be used. However, I feel the chosen methodology can construct a valid and reliable answer.

Throughout this thesis, I will use words such as: deals, takeovers, transactions, mergers and acquisitions interchangeable. This is especially true in the literature review where I used the language from previous researchers on the topic to present their findings. I know that the definition of a merger and an acquisition in theory differ but for this thesis the difference is irrelevant. In separation of bidders and target, bidders are defined as the continuing companies and targets as the acquired ones.

2 Literature review

M&A is a popular topic within the field of finance and financial literature. Especially the question if M&A is value creating or not keep popping up in the ever-increasing amount of research. I have decided to look specifically at the short-term value creation around the announcement date of a transaction. Most previous researchers study short-term value creation using an event study approach and they frequently extent their research to include possible value drivers. This extension is often done through cross-sectional regression analysis.

Short-term value creation in M&A is a popular topic in financial literature which numerous researchers have published papers on this topic. The majority have focused their research on specific geographical markets, where especially the US market is popular. Others have narrowed their research to specific industries. In Europe, most literature has been focused on the UK, but also continental Europe have been examined. I have found comparable research for the European market, with the most recent paper published by Martynova & Renneboog (2011) looking at the fifth merger wave from 1993 to 2001. For the US market, I have found more recent papers among them is Alexandridis, Antypas, & Travlos (2017). I believe that the findings and key points from those papers, along with the results from others, can be used for comparison to my findings.

The question if M&A is value creating for the bidder shareholders have not yet reaches a definitive conclusion. Campa & Hernando (2004) found that the CAR (cumulative abnormal return) for bidders were null in a sample of 262 transaction between 1998 and 2000 in Europe. This finding is supported by Eckbo & Thorburn (2000) that analyzed Canadian takeovers. Also, Bruner (2002) and Franks, Harris, & Mayer (1988) came to conclude zero CAR for bidding firms in the UK and US. Walker (2000) and Hazelkorn, Zenner, & Shivdasani (2004) both find negative CAR for the bidding firms. Walker (2000) found an average CAR of -0.84% studying 278 US deals between 1980 and 1996.

Hazelkorn el at. (2004) found that bidders on average lost between 0.5% and 0.7% in a sample with 1547 transaction in the US market between 1990-2002. Mulherin & Boone (2000) also support negative CAR to bidders, with a finding of -0.37%. Other researchers have found a positive CAR for bidding firms. Alexandridis, Antypas, & Travlos (2017) found positive and statistically significant abnormal returns of 1.05% for bidders in US deals between 2010-2015. This finding support the previous findings by Martynova & Renneboog (2011) and Goergen & Renneboog (2004), who found positive bidder CAR in Europe and Bradley, Desai, & Kim (1988) in the US of 0.97%. Thereby concluding that comparable literature has been unable to give a definitive answer to whether M&A is value creating for bidder shareholders.

More agreement among researchers is found, when looking at evidence for value creation for target shareholders. Here the evidence is more consistent across different markets and time periods. Unanimously all previous researchers find statistically significant abnormal returns to target shareholders. These abnormal returns are due to the large premiums paid by bidders. Bradley, Desai, & Kim (1988) found a 32.0% abnormal return for targets in the US. At the same time in UK Franks, Harris, & Mayer (1988) found a 20.8% abnormal return. More recently Houston, James, & Ryngaert (2001) found an abnormal return of 24.6% in a US sample between 1991 to 1996. Also, Campa & Hernando (2004), who determined bidder CAR of null, found target CAR of 9% in an event window of one month in a 1998-2000 European sample. Outside of US and Europa Diepold, Feinberg, Round, & Tustin (2008) found a positive CAR for target shareholders in the Australian market. Most recent Alexandridis, Antypas, & Travlos (2017) found a 29.32% CAR for target shareholders in the US between 2010 and 2015.

Previous researchers have often looked at specific characteristics of M&As to test if some are more value creating than others. One of the more popular characteristics to analyze is the strategy behind takeovers, or more specifically whether a takeover is done to focus or diversify a business. A focused strategy is, when firms use M&A as a growth strategy to increase market share, either by acquiring domestic competitors, or foreign firms within the same industry to enter new markets. A diversifying strategy is a strategy used to lever risk of operations and acquire new competencies. Previous researcher mostly agrees that a focused M&A strategy has better synergy effects than a diversifying one and thereby result in higher abnormal returns. Walker (2000) found losses the US bidders are primary limited to those participating in diversifying acquisitions. Healy, Palepu, & Ruback (1992) found that for US firms “*The performance improvement is particularly strong for firms with highly overlapping businesses*” They argue that the reason behind those results is such takeovers create good opportunities for economics of scale (Ibid, p. 161). Moeller & Schlingemann (2005), also found that diversifying takeovers create less value and takeovers which increase the level of both global and industrial diversification are performing worse than takeovers that only diversify on one level. Further these findings are supported by Doukas, Holmén, & Travlos (2001), who used a Swedish sample between 1980 and 1995. Also, Martynova & Renneboog (2006) and Goergen & Renneboog (2004) found focused M&A to result in higher bidder abnormal returns than diversifying M&A in Europe.

Method of payment as a value driver is one of the most discussed in M&A literature. The method selected can have a significant impact on the announcement effect for both bidder and target. Myers & Majluf (1984) invented the pecking order theory saying managers would prefer to finance projects with internal funds, rather than issuing debt and lastly issuing new equity. This due to investors interpret the firm’s action rationally, when managers have superior information and stock is issued to finance investments then stock prices will fall, other things equal. If the firm instead opted to issue debt to finance investments than stock prices will increase. This effect, known as the signaling effect, has been confirmed by several researchers through time. Shleifer & Vishny (2003) and Savor & Lu (2009) all found that overvalued companies, who expect future negative shareholder returns, have incentive to use their stock as currency. Travlos (1987) found a statistically significant difference between negative abnormal returns for stock financed takeovers and normal returns in cash financed takeovers. Eckbo, Giammarino, & Heinkel (1990) found that the abnormal return for bidders in US and Canada is monotonically increasing and convex in the fraction of the total offer that consist of cash. Same conclusion was reached by Martynova & Renneboog (2006), who found cash payments to outperform mixed payments, which again outperformed stock payments in terms of abnormal return for European bidders. Franks, Harris, & Mayer, (1988) found evidence that cash financed takeovers outperform stock financed takeovers in both the UK and US. More recent Servaes (1991), Sudarsanam & Mahate (2003) and Alexandridis, Petmezas, & Travlos (2010) all found the market reacts differently to different payment methods and generally favor cash over stock due to the signaling effect. This signaling effect was analyzed by Li (2018), who found the difference between abnormal returns for cash and stock takeovers is due to two effects: signaling and wealth transfer. Li found that signaling causes 94% of the negative abnormal return for stocks takeovers and that the wealth transfer from debt holders to stockholders caused 100% of the gains in cash takeovers. Cash takeovers often require the acquirer to issue debt, which means the risk for existent debt holders increases and wealth is transferred to stockholders. Whereas stock financed takeovers requires issuing new stock, diluting existing stock but also decreasing risk for debt holders, who in case of bankruptcy have priority rights to assets and thereby transferring wealth from stockholders to debt holders.

M&A is often used as a growth strategy for businesses, and the choice is between growing domestically or abroad in new markets. Depending on which strategy is selected, it might have an impact on the value creation for shareholders. Choosing cross-border acquisitions have several pros and cons. Often the geographical diversification is great for levering risk, and the possibilities which new markets bring are good Sudarsanam (2003). But adjusting to foreign regulations, taxes and culture can prove to be difficult. Eckbo & Thorburn (2000) found that domestic bidders for Canadian targets earned positive abnormal returns, which are statistically significant, and foreign American bidders earn abnormal returns that was indistinguishable from zero in their sample consisting of 9,294 bids between 1945 and 1983. On the contrary to this finding Lowinski, Schiereck, & Thomas (2004) and Hazelkorn, Zenner, & Shivdasani (2004). Lowinski el at, (2014) have found no statistical significant difference between cross-border and domestic acquisitions in Switzerland. Arguing that international capital markets are too integrated for there to be a difference. Harris & Ravenscraft (1991) support this, and argue that the expected difference in abnormal returns between domestic and cross-border acquisitions is zero, provided that the capital and factor markets are segmented internationally. Whereas Hazelkorn el at, (2004) found that cross-border acquisitions created more value than domestic acquisitions do in the US. They point out the opportunities that entering new markets create such as more consumers, possibilities for local sourcing and production as the reasons for cross-border to outperform domestic acquisitions. Although previous researchers found contradicting evidence between cross-border and domestic acquisitions, a consensus is emerging. Some of the most cited papers on this topic Martynova & Renneboog (2006), Goergen & Renneboog (2004) and Moeller & Schlingemann (2005) all find supporting evidence of domestic acquisitions yield higher abnormal returns than cross-border acquisitions for both the US and the European market, and the difference is statistically significant. Goergen and Renneboog (2004) find this surprising as foreign direct investment theories predict foreign bidders may be able to take advantage of imperfections in factor and capital markets and thereby generate higher abnormal returns for shareholders.

Another characteristic that previous researchers have observed is the bidder's cash flow prior to acquiring a target. Jensen & Meckling (1976) presented in their now famous paper a theory that agency costs arise, when managers are reluctant to pay out excess cash to shareholders, instead opting to invest in negative NPV (net present value) projects. Later Jensen M. C. (1986) derived the free cash flow (FCF) hypothesis saying that firms with high cash flows more often make value destroying acquisitions. Some researchers have since tested this, among them is Lang, Stulz, & Walkling (1991), who found supporting evidence in an US sample. They used Tobin's Q to distinguish between firms that have good investment opportunities and firms that do not, where good investment opportunities imply a low q. They found that firms with low q[1] have abnormal returns, which is negatively related to free cash flows. Also, Uysal (2011) accepts parts of the free cash flow hypothesis in his paper. He found that overleveraged firms pay lower premiums, and yield more favorable announcement returns this is all in accordance with the FCF hypothesis. However, he fails to find evidence to unfavorable market reactions to underleveraged acquirers in both the short and long run. Chu & Liu (2016) found that firms with either high cash flows or large cash reserves pay higher premiums for target in the real estate industry. Owen & Yawson (2010) and Harford (1999) are supporting this, they all found a negative relation between cash rich firms and bidder returns. Contrary to the long list of researchers supporting the free cash flow hypothesis is Chandera & Setia-Atmaja (2014). They found that bidder's cash flow is marginally positively associated with shareholders' return, which is consistent of the pecking order theory, but contradicts the free cash flow hypothesis.
Regarding target cash flows, the amount of literature is more limited. However worth noticing is Jensen M. C. (1986), who conclude that targets with high cash flows are excellent candidates for a leveraged buy-out because they can support large debts and are therefore favored as targets by private equity firms.

3 Theory and hypotheses formulation

Inspired by the results of previous researchers, M&A theory and my own interest, I have formulated a set of hypotheses. The hypotheses will act as a guideline for my own empirical research and are based on the most important aspects and characteristics of short-term value creation in M&A.

[1] Low q is defined by Lang, Stulz & Walkling (1991) as a q value less than 1.

3.1 Value creation in M&A

I want to research the CAR for both bidders and targets in hypotheses 1.1 and 1.2. The results of these two hypotheses will be the core of the following analyses. As the CAR for bidders and targets will be used as the dependent variable in a cross-sectional regression analysis testing for value drivers. This will be further explained in the methodology section of this thesis. The literature review indicated, that previous researchers were unable to agree if M&A is value creating for bidders. Although most found that the abnormal return for bidders is either insignificant, or very small. Consequently, I develop the first hypothesis:

Hypothesis 1.1: Bidder abnormal return is zero in the event window

Previous research presented strong and consistent evidence for positive and significant abnormal returns for targets. Therefore hypothesis 1.2 is formulated as:

Hypothesis 1.2: Target abnormal return is positive in the event window

3.2 Method of payment

The method of payment as an impacting factor on shareholder returns is widely studied. For both the US and the European market evidence from the literature review suggest that cash transactions outperform stock transactions in terms of abnormal returns. This fit well with the signaling theory, which predict decreasing stock prices, when new stocks are issued due to investors, who see this as a signal from managers that the stock is overvalued. Besides the signaling effect shareholders also prefer cash as payment method because cash effectively increases leverage and thereby signal confidence in future performance from management. Based on the previous findings and theory I formulate hypothesis 2.1 as:

Hypothesis 2.1: Cash transactions result in higher bidder abnormal returns than stock transactions

As for the target company the signaling theory still apply. Assuming bidders would never use an undervalued shock as a mean of payment. Thus, the choice is between cash and overvalued stock, the target shareholders would face a lower risk and higher return be receiving cash as payment. Based on this, I have formulated hypothesis 2.2 as:

Hypothesis 2.2: Cash transactions result in higher target abnormal returns than stock transactions

Not all transactions are completed using pure cash or stock as payment. Some also uses a mix of both to finance the transaction. Martynova & Renneboog (2006) both found that mixed payment yield higher abnormal returns for than pure stock payment. And Eckbo, Giammarino, & Heinkel (1990) found that abnormal returns increase in the fraction of total payment consisting of cash. Thus, hypothesis 2.3 and 2.4 are formulated as:

Hypothesis 2.3: Cash payments result in higher bidder abnormal returns than mixed payments

Hypothesis 2.4: Cash payments result in higher target abnormal returns than mixed payments.

Hypothesis 2.3 can be tested through the same regression model as hypothesis 2.1, and hypothesis 2.4 can be tested together with hypothesis 2.2.

3.3 Focused vs. Diversifying M&A

When firms decide whether to participate in focused or diversifying M&A, they look at which transactions that bring the most synergies with them. The literature review revealed strong evidence from previous researchers, that synergies from focused acquisitions create more shareholder value than the synergies from diversifying acquisitions. These results were consistent across several markets including Europe and US (Walker, 2000) and (Goergen & Renneboog, 2004). These academic findings apply well to the practical M&A history. Martynova & Renneboog (2008) who researched merger waves found, that the third wave starting in the 1950 build many conglomerates. Where the fourth wave from 1981 resulted in an unprecedented number of divestures, mainly due the conglomerate structure had become inefficient to compete with more modern streamlined firms. Based on this I formulate hypothesis 3.1 as:

Hypothesis 3.1: Focused acquisitions result in higher bidder abnormal returns than diversifying acquisitions

Return for target shareholders is a lesser researched topic than bidders' return. Martynova & Renneboog (2006) found that targets being acquired as part of a diversifying strategy receive higher abnormal returns than those targeted for focused acquisitions. They argue bidders are more aggressive in their bidding and often end up overpaying for unrelated firms, meaning they acquire for the sake of diversification rather than value creation. Hence, I formulate hypothesis 3.2 as:

Hypothesis 3.2: Diversifying acquisitions result in higher target abnormal returns than focused acquisitions

To distinguish between focused and diversifying transactions, I have obtained the SIC (Standard Industrial Classification) code for each bidder and target. The SIC code is a uniform system used to classify industries and companies, developed by the United states, but used in many other countries. The system begins with 0100 and ends with 9999, where the first two digits indicate the overall industry like mining, manufacturing, retail, finance etc. The last two digits indicate the sub-industry classification for a company. If the bidder and the target have same two first digits of the four-digit code, then the transaction is considered intra-industry i.e. focused acquisition. If the first two digits are different the transaction is considered diversifying.

3.4 Domestic vs. Cross-border M&A

Previous researcher seems to be unable to come up with a unified conclusion for, which is the better strategy. Moeller & Schlingemann (2005), Martynova & Renneboog (2006) and Diepold, Feinberg, Round, & Tustin (2008) all found evidence in favor of domestic acquisitions. Nevertheless, these findings contradict the FDI theory which suggest foreign bidders can take advantage of imperfections in capital markets and consequently earn higher abnormal returns (Goergen & Renneboog, 2004). This theory is supported by findings from Hazelkorn, Zenner, & Shivdasani (2004), suggesting cross-border acquisition increase abnormal returns in the EU. I have been unable to find further support for this theory, and Aevoae, Dicu, & Mardiros, (2018) might have an explanation for why. They found that the effects from FDIs are the greatest in developing markets compared to developed markets.

The Western European market is considered a highly-developed market, thus small or zero positive effects from FDIs can be expected. Lowinski, Schiereck, & Thomas (2004) found no difference between cross-border and domestic acquisitions. They argue that differences will only occur, if market imperfections are present. In many ways, the Western European market is integrated and homogenous, but differences in legal systems, currencies and cultures make individual countries unique. This is observed by researchers, researching the European market. Goergen & Renneboog (2004) found that when a UK firm is involved as target or bidder, the abnormal return is higher than for continental European countries, this finding is supported by Martynova & Renneboog (2006). Moeller & Schlingemann (2005) find differences in abnormal returns which depend on the level of shareholder protection in the legal system that governs the market. Statistically significant differences between French civil law and English common law were discovered. Further not all Western European countries are members of the European Union (EU), which hinders the flow of capital from non-member states to member-states, thus also lower the combined market efficiency in my sample. From these findings, I hypothesize the European market is not yet fully integrated and efficient, and therefore I expect to observe a difference in abnormal returns from cross-border and domestic acquisitions which align with previous researchers' conclusions. Hypothesis 4.1 is consequently formulated as:

Hypothesis 4.1: Domestic acquisitions result in higher bidder abnormal returns than cross-border acquisitions

I find the idea by Goergen & Renneboog (2004) regarding FDI theory and foreign bidders' advantages from market imperfections interesting. However, since my sample covers Western Europe, a market that is regarded as relatively, but not fully efficient and integrated, with only minor imperfections, I formulate hypothesis 4.2 based on the previous results from Martynova & Renneboog (2006) and Moeller & Schlingemann (2005), thus hypothesis 4.2 is formulated as:

Hypothesis 4.2: Domestic acquisitions result in higher target abnormal returns than cross-border acquisitions

3.5 Cash flows

The free cash flow hypothesis is presented by Jensen M. C. (1986) and elaborated upon in the literature review, indicate firms with high free cash flows are more prone to make bad acquisitions. It seems they neglect proper due diligence before acquiring a target. Such due diligence would have been done, if the acquisition was funded by external funds like bank debt or stock issue, because the external monitoring of management would increase. Internal funding of investments imply management to hold more control and decrease monitoring, which can lead to agency problems. Whether management is acting in self-interest or is simply overconfident, is hard to answer, but both can lead to value destroying decisions. By this theory hypothesis 5.1 is formulated as:

Hypothesis 5.1: High bidder cash flows will have a negative effect on bidder abnormal returns.

Jensen M. C. (1986) also argues that a firm with high cash flows makes an excellent target, because this firm can support large debts. Such firms are consequently often targets for private equity firms, using leveraged buy-outs to acquire them. While industrial buyers might not seek the same attributes in targets as private equity funds, a steady high cash flow is worth paying a premium for. Therefore, I formulate hypothesis 5.2 as:

Hypothesis 5.2: High target cash flows positively affect target abnormal return

4 Methodology

4.1 Introduction

For this research paper to be reliable it is crucial that it can be replicated in the future to yield the same results. Therefore, the methodology section describes all the important procedures in detail, so readers can follow and replicate the research for future comparison. The analyses of this thesis will consist of two parts. First an event study where I estimate CAR for each firm in the data sample. The results from the event study will be used to test hypotheses 1.1 and 1.2. In the second part the calculated CAR will function as the dependent variables and be regressed with various independent variables. Consequently, the second part depend on the results obtained in the event study. The second part will test hypotheses 2.1 to 5.2. In this methodology section I will begin by explaining the event study methodology used and then proceed to the cross-sectional regression analysis methodology.

4.2 Event study methodology

There are several techniques to assess the impact from M&A on firms, and no method is more accurate or resolute than others. I have chosen to study the stock price development for each firm in and around the announcement date for the transaction using an event study. Event studies are used to assess the short-term impact from a single event on the stock price. The usefulness of an event study comes from the fact, that, given rationality in the market place the effect of the event's economics impact will be reflected immediately in the stock price (Campbell, Lo, & MacKinley, 1997). Or in other words, event studies work because markets are efficient.

The event study assesses the abnormal return for a firm in the period before, during and after an event that impact the stock price occurs. Such events can be earning announcements, equity issues, CEO replacements and M&A announcement, which is the case in this thesis. Further event studies have been used to assess the impact on stock prices, from new regulations and policies. Thereby indicating the method is not limited to microeconomic events, but can be extended to include macroeconomic events as well. One of the most well-known event studies and building stone for many of the event studies conducted in the last half a century is Fama, Fisher, Jensen, & Roll (1969), who studies the impact from stock splits. This study is based in the efficient market hypothesis as well as anticipating the market to evaluate new information in an unbiased manner. Assuming markets are 100% efficient, and that no information is leaked prior to the event, is a strong assumption to make. By extending the event window beyond the announcement date one can implicitly assume a semi-efficient market. Extending the event window also captures stock movements from the event, if it is announced after the market has closed.

By comparing the actual observed return in the event window with the calculated expected normal return I can test whether M&As have a direct impact on the stock price or not, and thereby assess, if it is value creating or not. I Consider the expected normal return, which will make the event study method more sophisticated, rather than just to look at the stock price reaction at announcement, because it filters out all other factors that the whole stock market experiences. That is leaving only the abnormal return that reflect the real value-impact from the M&A announcement.

4.2.1 Event study in a six-step process

The outline of an event study presented by Campbell, Lo, & MacKinley (1997) and MacKinley (1997) initially include 7 steps whereas the event study model by Bowman (1983) has 5 steps. Both have many overlapping aspects and are essentially adjusted to the specific research the authors conduct. I have drawn inspiration from both and formulated a six-step model that fits my M&A announcement research.

1) Event definition
2) Determine event window and estimation period
3) Calculate normal returns
4) Calculate abnormal returns and accumulate
5) Testing procedures
6) Interpretation and conclusions

In step one, I define the event in question, including expectations and limitations for transactions to be included in the data sample. In step two, I determine the event window and the estimation period. When determining the event window, it is very important to think about when the market has received the transaction announcement because it is crucial to be included in the event window. The estimation period should reflect the true market reactions to the firm and not include the event window. This is to prevent the announcement from influencing the normal performance model and for the sampling errors in the coefficients to equal zero. In the third step the normal returns are calculated, this can be done by several models. I will choose the most appropriate one. Fourth, the abnormal returns are measured by using the actual returns observed in the event window and subtracting the normal returns calculated in step three. The abnormal returns are accumulated within the event window to find the cumulative abnormal returns. Step five is to analyze and test the CAR statistically. In Step six the results from step five is interpreted and compared with previous finding to draw conclusions.

4.2.1.1 Event definition

The event in question is the announcement of a transaction in which a bidder acquire control over a target. The transaction must be announced before the end of 2018. Therefore, no tender offers or incomplete transactions will be included in the data sample.

4.2.1.2 Determine event window and estimation period

The estimation period is used to calculate the expected normal return for stocks. For my thesis, I have selected an estimation period of 200 days equal to approximately 9 months of trading. In general, the norm is between 120-240 days which correspond to 6-12 months of trading. MacKinley (1997) suggests 120 days, Goergen & Renneboog (2004) uses 195 days and Martynova & Renneboog (2006) uses 240 days. My estimation period will run from 211 trading days prior to the announcement date to 11 days prior to the announcement date. By selecting a long estimation period, I assume the period captures the true market return of the stock, and thereby avoiding sampling errors in the coefficients for the model used to calculate normal returns, because the variance of the error term should in theory approach zero, however other events happening during the estimation period can also affect the calculated normal return. By MacKinley's notation T_0 marks the first day of the estimation period, with t as daily notation for time. The estimation period starts at T_0 and ends at T_1. The estimation period length is defined as $L_1 = T_1 - T_0$.

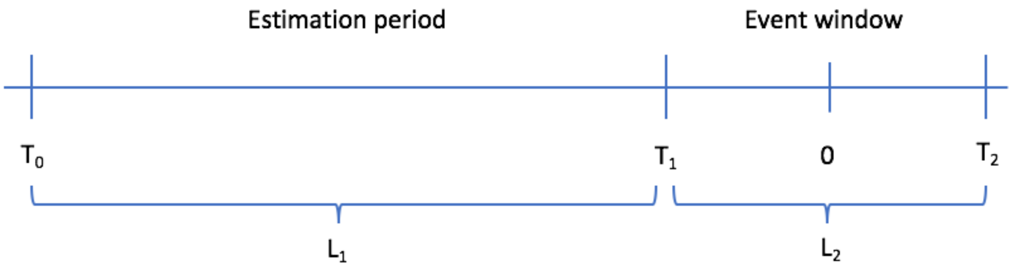


Figure 1: Estimation period and event window

The event window which capture the abnormal return from the announcement begin a short time prior to the announcement date and ends an equal short time after the announcement. The event window is extended beyond the event date itself to capture slow reactions in the stock price caused by the announcement, market expectations and to consider that sometimes information about the transaction is leaked or creates rumors a few days prior to official announcement. Ball & Brown (1968) found that 85-90% of the effect from new information had already been included in the stock price before the announcement. They stated that investor expectations were the main reason for the stock price development prior to announcement. The norm for the length of the event window is between -1,+1 day and -10,+10 days of the event date (Graca & Masson, 2016) and (Brown & Warner, 1985). Where -10,+10 days refer to a period from 10 days prior to announcement to 10 days after announcement. MacKinley (1997) suggests only to define the event window as -1,+1 day. I have decided for formulate four event windows to test the sensitivity of the results, my event windows are as followed: -1,+1 day as MacKinley, -2,+2 days, -5,+5 days and -10,+10 days. The event window is defined as L_2 and start at T_{1+t} and end at T_2 and is illustrated in figure 1 above.

4.2.1.3 Calculate normal returns

There are several methods that can be used to estimate the expected normal return of a stock. However, as it is impossible to predict the future none of the models can give a 100% correct price. Like the clear majority of previous researchers, I have selected the market model to calculate the expected normal return. Below I will introduce some of the other available models before elaborating upon why the market model is the optimal choice.

There are two types of models to predict expected return: statistical and economic models. Models from the statistical category follow statistical assumptions about the behavior of asset returns and do not depend on any economic arguments (Campbell, Lo, & MacKinley, 1997). Where economic models rely on investor's behavior and are not solely based on statistical assumptions, although economic models in practice also depend on statistical assumptions. Thus, the potential advantage of economic models is not the absence of statistical assumptions (Ibid). Statistical models are more often used, and they assume stock returns are jointly multivariate normal and independently and identically distributed through time. The Constant-Mean-Return model is a simple statistical model, where the expected return for stock i is given by:

$$R_i = \mu_i + \varepsilon_i$$

Eq: 1

Where $\mu_i$is the average return for stock i and E$[\varepsilon_i]$ = 0. This is in practice done by averaging the daily returns in the estimation period, which means this model assumes, that the past is the best predictor for the future. Although the constant-means-return model is considered a simply model, Brown & Warner (1985) found that it often yields results, that are close to those of more advanced models. They attribute this finding to the fact, that the variance of abnormal returns is very often not reduced much by choosing a more advance model. A weakness to the constant-mean-return model is, that it does not factor in the portion of return which is related to variations in the market's return.

An example of an economic model is the cross sectional CAPM (Capital Assets Pricing Model). It predicts that the expected return of an asset is a linear function of its covariance with the return of the market portfolio Campbell, Lo, & MacKinley (1997). The CAPM method was widely used in event studies in the 1970s (Ibid). The reason for its diminishing popularity is found in discoveries, that cast doubt on the validity of the restrictions imposed by it such as investors behavior, further the CAPM has problems with parameter stationarity. Such troubles are easily overcome by choosing the market model, which have prediction errors that are assumed to be zero for any size of sample firm (Seyhun, 1986). Further Banz (1981) and Reinganum (1981) find that the residuals are on average positive for small firms and negative for large firms, and such systematic bias can lead to biases in estimating the abnormal return. Due to both the problem with the residuals in the cross sectional CAPM model and the Constant-Mean-Return model not considering market variables and systematic risk I have opted to use the market model. This model is also favored by some of the most cited previous researchers, including: (MacKinley, 1997), (Martynova & Renneboog, 2006), (Goergen & Renneboog, 2004) and (Alexandridis, Antypas, & Travlos, 2017). The results by Brown & Warner (1985) are interesting, therefore I have decided to calculate the expected normal return and the abnormal return using the constant-mean-return model as a sensitivity/robustness analysis and compare the results to those of the market model.

The market model regresses the market return on the individual stock return. Consequently, the market model is a time series regression which models the return of the individual stock as a linear function of the market return over time. A time series regression between returns can follow a basic static model relating y to z (Wooldridge, 2009):

$$y_{it} = \beta_0 + \beta_{1t} * z_{1t} + \varepsilon_{it}, t = 1,2, \ldots, n$$

Eq: 2

Where "t" is the notation for time in day, i.e. t = 1 day and "n" is to total number of observations, i.e. number of days in which the returns for stock i are observed. Adjusting the notation, I get the equation used in the market model to calculate the expected normal return for an individual stock i (R_{it}) from the market return (R_{mt}).

$$R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it}$$
$$Where\ E(\varepsilon_{it}|X_t) = 0\ and\ Var[\varepsilon_{it}] = \sigma_t^2$$

Eq: 3

For the time series regressions in my thesis I will use a classic OLS (Ordinary Least Squares) regression to estimate the individual stock return from the market return. OLS fits a linear regression line with the observations, so that the SSR (sum of squared residuals) is minimized. The residuals are equal to the distance between the observations and the regression line estimates and are embodied in the error term. Therefore, the lower the SSR the better the models fits the data.

When I use time series data instead of cross-sectional data for regression analysis I must consider some key assumptions (Wooldridge, 2009) and (Stock & Watson, 2015).

1) Linear in parameters
2) Zero conditional mean
3) No perfect collinearity
4) Homoscedasticity

5) No serial correlation
6) Outliers

The next section will explain how the assumption alter the OLS regression from cross-sectional data to time series data.

First, since time series data is stored in arrays with N rows, and K columns. Where N is the number of days observed and K is the total number of transactions. As data is linear in time the regression model should be linear in its parameters.

Second, ideally the data should be strictly exogenous, meaning that the error term at time t ε_t is uncorrelated with each explanatory variable at every time-period. Obtaining a data set that is strictly exogenous is a best-case scenario that one can only hope for. For my thesis, this would imply the error term cannot be correlated with the market return, which can happen due to economic shocks or systematic risks. Selecting a large sample over a longer time-period can help overcome or limit this issue. Consequently, I have included all transactions from my sample period in my gross sample thus, I assume this will not impact my results significantly.

Third, explanatory variables are allowed to be correlated, but not perfectly correlated. Meaning correlation coefficients of +1 and -1 are not accepted into the model. For this part of my thesis collinearity is not a problem as I only have one explanatory variable which is the market return. However, some stocks are traded infrequently which causes the daily returns to be zero and in turn correlation to be high. To account for this, I omit stocks that is not traded at least three out of four days in the estimation period.

Fourth, homoscedasticity implies the variance of the error to be constant across any time-period. If the variance of the error term is not constant over time, but rather move with the parameters of the model, the model suffers from heteroscedasticity. Heteroscedasticity does not lead to biased regression coefficients but the standard deviation of the estimators will be, thus impacting t-statistics and p-values. In estimating CAR in this part of my analysis I am not using the standard deviations, therefore heteroscedasticity is not an issue here. However, when testing the CAR for statistical significance in the analysis part I do use the standard deviations, therefore I will run a test Breusch-Pagan test in that part of the analysis to see if my models suffers from heteroscedasticity.

Fifth, no autocorrelation / Serial correlation is allowed in the model. Autocorrelation appears in time series data when Y in one period is correlated with its value in the next period, or in other words the time-series is correlated with its own history. The first autocorrelation is the correlation between Y_t and Y_{t-1} and is the most common type of autocorrelation. The second autocorrelation is between Y_t and Y_{t-2} and so forth (Stock & Watson, 2015). This is great for building a forecasting model, because you can use past values to predict future development. For my thesis autocorrelation constitute a problem if it makes the error term follow a pattern. When the error term follows a pattern, it indicates that something is wrong with the model, i.e. that something is missing (Halcoussis, 2005). Autocorrelation is measured by the i^{th} sample autocovariances and variance (Stock & Watson, 2015).

$$\widehat{cov(Y_t, Y_{t-1})} = \frac{1}{T}\sum_{t=i+1}^{T}(Y_t - \bar{Y}_{i+1:T})(Y_{t-i} - \bar{Y}_{1:T-i})$$

$$\hat{\rho}_i = \frac{\widehat{Cov(Y_t, Y_{t-1})}}{\widehat{var(Y_t)}}$$

Eq: 4

In general autocorrelation does not create a problem because I look at stock returns. This comes from the fact that developments in the daily stock prices is not based on whether the stock went up or down yesterday. Stocks react to all news and information that impacts the company for which the stock represents the value, meaning the error term should have an average of zero and not follow a pattern. If it follows a pattern, autocorrelation is present. The problem is that OLS regression by function always make the average of the error term equal to zero, thereby making autocorrelation undetectable. However, autocorrelation can exist in stock returns, if the underlying stock is a momentum stock or a thin traded stock. The thin trading problem is solved by excluding stocks, that has not been traded in more than one out of four days in the estimation period. Momentum stocks constitute a problem, because they follow an irrational behavior. Investors purchase the stock only because it went up yesterday, and the day before yesterday, which causes a hype around it. To figure out if autocorrelation is present in any of my time series, I have plotted the residuals for all time-series for both bidders and targets. None of these residuals show any clear sign of patterns. The plots of all residuals are included in the data package for this thesis.

Lastly, outliers are a cause for problems as OLS regression is sensitive to large outliers. Therefore, any data mistakes, such as a missing stock price for a day, which will yield a return of +100% or -100% is a problem. Such mistakes will affect the beta used to calculate the expected normal return.

4.2.1.4 Calculate abnormal returns and accumulate

Once the expected normal returns have been calculated in the previous step, finding the abnormal return is easy. In the market model explained above in equation 3, that the expected normal return is given by:

$$R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it}$$

Where the alpha and beta represent the expected normal return and the error term represent the abnormal return i.e. the unexpected return. Rearranging the above I get

$$\varepsilon_{it} = R_{it} - \left(\widehat{\alpha_i} + \hat{\beta}_i * R_{mt}\right)$$

Eq: 5

and since the error term represent the abnormal return I can rewrite to:

$$\varepsilon_{it} = AR_{it}$$

$$AR_{it} = R_{it} - \left(\widehat{\alpha_i} + \hat{\beta}_{it} * R_{mt}\right)$$

Eq: 6

Finding the CAR for a stock is done by adding all the daily abnormal returns for each individual stock i in the event window, which was defined as L_2 raging from T_{1+t} to T_2 in section 4.2.1.2.

$$CAR_{it}(T_1 + t, T_2) = \sum_{t=T_1+t}^{T_2} AR_{it}$$

Eq: 7

The above equation shows the gains or losses to the shareholders of company i from the M&A transaction. Instead of only adding ARs for a firm across days in the event window, I can also add AR from a single day in the event window for all bidders or targets and divide by the number of transactions. This will yield the AAR (Average Abnormal Return):

$$AAR_t = \frac{1}{K}\sum_{i=1}^{K} AR_t$$

Eq: 8

Where K is to total number of transactions included in the analysis. By calculating AAR, I can specifically point out which day in the event window, that returns the most value to shareholders. In a perfect scenario, AAR should be zero for all days prior to the announcement of the transactions and be equal to CAAR (cumulative average abnormal return) on the day of announcement and then return to zero the days following the announcement. By extending the event window beyond the announcement day I consider a weaker form of market efficiency. Therefore, I can get an idea of how efficient the markets in Western Europe are by looking at the AAR day by day in the event window from -10 to +10. The CAAR is giving by:

$$CAAR_{it}(T_1 + t, T_2) = \sum_{t=T_1+t}^{T_2} AAR_t$$

Eq: 9

One can also use CAAR to see if more value is created prior to announcement date or after. This is done by starting or ending the CAAR on the announcement day i.e. event window = -10,-1 or +1,+10. The results can be used with the daily AAR results to test market efficiency.

4.2.1.5 Testing procedures

The next step is to test the statistical significance of the abnormal returns calculated in the previous step. Generally, when testing whether a variable is statistically significantly different from zero, you would use a parametric test, like a t-test (Bartholdy, Olson, & Peare, 2007). Although abnormal returns have by previous researchers been revealed to have fat-tails and be non-normally distributed (Fama E. F., 1976) and (Brown & Warner, 1985). To account for this MacKinley (1997) suggests applying a non-parametric test to complement the parametric test. Central limit-theorem predict, that the power of a parametric t-test depends on the mean and variance of the distribution of security returns, when the sample is large and not the shape of the distribution. For the t-test to be effective the distribution of returns must be normal. Ahern (2009) tested this and found the non-parametric tests perform better than the parametric tests because the non-parametric tests do not follow the normal distribution assumed by the parametric ones, thus the non-parametric tests work as a robustness check. The finding is supported by Campbell, Lo, & MacKinley (1997) and Kothari & Warner (2007). Further, events have been proved to introduce volatility in security returns, cross-sectional correlation between event-introduced volatility and abnormal returns are not considered in parametric tests (Kothari & Warner, 2007) (MacKinley, 1997) and (Campbell & Wesley, 1993). By including a non-parametric test such issue is minimized (Corrado C. J., 1989).

4.2.1.5.1 Parametric tests

The leading parametric test used in event studies to test statistical significance for abnormal return is the students' t-test (Ahern, 2009). The simplicity of the t-test combined with the statistical power it possesses makes it a common choice in event studies for researchers such as: (Brown & Warner, 1985), (Klinger & Gurevich, 2014) and (Martynova & Renneboog, 2006). I use the statistical software program "R" to compute the t-statistics and the corresponding significance levels to see, if I can reject H_0 of zero abnormal return and accept H_1 of positive abnormal return or vice versa.

For the AAR, the t-statistics is given by

$$t = \frac{AAR_t}{\sqrt{\sigma^2(AAR_t)}}$$

Eq: 10

Where the AAR and variance is given by

$$AAR_t = \frac{1}{K}\sum_{i=1}^{K} AR_t \qquad \text{and} \qquad \sigma^2(AAR_t) = \frac{1}{K^2}\sum_{i=1}^{K} \sigma_\varepsilon^2$$

For the CAR, the t-statistics is given by

$$t = \frac{CAR_i(T_1 + t, T_2)}{\sqrt{\sigma_i^2 CAR(T_1 + t, T_2)}}$$

Eq: 11

Where the CAR and variance is given by

$$CAR_i(T_1 + t, T_2) = \sum_{t=T_1+1}^{T_2} AR_{it} \qquad \text{and} \qquad \sigma_i^2\big(CAR_i(T_1 + t, T_2)\big) = L_2\sigma_{\varepsilon i}^2$$

Where the $L_2\sigma_{\varepsilon i}^2$ is just saying that the standard deviation for the CAR is equal to the length of the event window in days times the daily standard deviation.

For the CAAR, the t-statistics is given by

$$t = \frac{CAAR(T_1 + t, T_2)}{\sqrt{\sigma^2 CAAR(T_1 + t, T_2)}}$$

Eq: 12

Where the CAAR and variance is given by

$$CAAR(T_1 + t, T_2) = \sum_{t=t_1+1}^{T_2} AAR_t \qquad \text{and} \qquad \sigma^2\big(CAAR(T_1 + t, T_2)\big) = \sum_{t=T_1+1}^{T_2} \sigma^2(AAR)$$

4.2.1.5.2 Non-parametric tests

When previous researchers conduct non-parametric tests in event studies they often use the rank or sign test. I have chosen to use the rank test developed by Corrado C. J. (1989). The reason behind this decision is found in the results by Corrado & Zivney (1992). They found the rank test outperforms the sign test in a comparison between the two. The rank test will also solve the issues with cross-sectional correlation and non-normal distribution of abnormal returns.

The rank test is conducted by ranking all abnormal returns from both the estimation period and the event window. In the cases where AR = 0 ranks are often tied, in these cases the mid-range of the rank is used. After ranking all the observations, they are standardized between 0 and 1 with mean 0.5. The rank test is performed by testing if the average rank of the abnormal returns in the event window is higher than the mean of 0.5. If the event window average is above 0.5 with statistical significance the rank test conclude that abnormal returns are present. The first step to performing the rank test is, for each bidder and target, to rank each of the daily abnormal returns against all the other daily abnormal returns for that company. This is done by using the Rank() function in excel. Next step is to standardize the rank:

$$R_{it} = 1 - \frac{Rank(AR_{it})}{1 + L_1 + L_2}$$

Eq: 13

Where R_{it} is the standardized rank value and Rank(AR) represent the rank in each AR from the observations within a firm. I divide rank by $1+L_1+L_2$ to standardize between 0 and 1. The standardization is done to obtain a sample mean of 0.5. Corrado C. J. (1989) denotes the standardized rank by K_{it}, however, since I use K to denote total number of transactions, I opt to use R Instead. The standardized rank value is subtracted from 1, this is done so the highest daily AR is ranked as 1.00 and the lowest as 0.00. The variance for R_{it} for each individual company is calculated as:

$$\sigma_{Ri}^2 = \frac{1}{L_1 + L_2} \sum_{t=T_0}^{T_2} (\overline{R_\iota} - 0{,}5)^2$$

Eq: 14

The individual variance is calculated to obtain the sample standard deviation used to derive the t-statistics for significance testing, the 0.5 represent the sample mean. The initial rank test developed by Corrado was a single day test. Campbell & Wesley (1993) presented a simple model that could be extended to a multiday event window:

$$\bar{R}\,(T_1 + t, T_2) = \frac{1}{L_2} \sum_{t=T_1+t}^{T_2} R_{it}$$

Eq: 15

By applying the eq. 15 I can sum average ranks both cross days in the event window for individual companies and across all companies (k bidders and k targets).

The abnormal return is tested for statistics significance by applying the following t-statistics:

$$t_{rank} = \sqrt{L_2} * \left(\frac{\bar{R}(T_1 + t, T_2) - 0{,}5}{\sigma} \right)$$

Eq: 16

Where the sample standard deviation is calculated as the square root of the sum of all the individual variances calculated in eq. 14 divided by the total number of firms. Mathematically stated as:

$$\sigma = \sqrt{\frac{1}{K} * \sum_{i=1}^{K} \sigma_i^2}$$

Eq: 17

The rank test proves abnormal return if the event window average is above 50% (i.e. average R in event window is above 0.5) with statistical significance measured by the t-statistics. Now the reason for subtracting the standardized rank from 1 becomes clear as it means that the higher the average rank the higher the abnormal return.

4.2.1.6 Interpretation and conclusions

The parametric t-test will test if the observed abnormal return is statistical significant. If the t-statistics in a two-sided test, is high enough, then H_0 of zero abnormal return is rejected and I can conclude M&A activities are value creating. The coefficient will tell how high or low the abnormal return is for the sample population. The t-test assumes the abnormal returns are normally distributed, which have been proved to be an unreliable assumption. To overcome this issue the rank test is applied and will tell if the abnormal returns in the event window is statistically higher than the abnormal returns in the estimation period. By ranking all the return from 1.00 to 0.00. If the average for the event window is above 0.5 it indicates that M&A activities are value creating and if the average is below 0.5 it indicates negative returns from M&A activities. Whether the results are statistically significant or not depends on the t-statistics.

4.3 Cross-sectional regression analysis

Cross-sectional regression is used to test the second part of the hypotheses (Hypothesis 2.1 to 5.2). The dependent variable in the analysis will be the CARs for bidders and targets. The independent variables will be the potential value drivers, that was explained in the literature review and elaborated upon in the hypothesis formulation section. To avoid omitted variable bias in my regression analysis I am going to include control variables. Thereby making the regression analysis a multiple regression analysis.

Multiple regression analysis can help me to point out possible causalities between variables, where normal regression analysis would provide misleading results. By regressing CAR with control variables, I get results on which of these variables impact CAR, and which have the biggest impact on value creation through M&A. In general, multiple regression analysis with n number of variables can be written out the following way:

$$Y = \beta + \beta_1 * X_1 + \beta_2 * X_2 + \cdots + \beta_n * X_n + u$$

Eq: 18

For this thesis, the above can be rewritten as:

$$CAR(T_1 + t, T_2) = \beta + \beta_1 * X_1 + \beta_2 * X_2 + \cdots + \beta_n * X_n + u$$

Eq: 19

To use Ordinary Least Squared (OLS) regression to make an approximation of the regression function from my data sample for the general data population, I must ensure the OLS assumptions are satisfied (Stock & Watson, 2015). The OLS assumptions include the following:

1) Linearity in parameters
2) Random sampling
3) No perfect collinearity
4) Zero conditional mean
5) Homoscedasticity

6) Outliers

The first assumption simply states, that the model presented above must be linear in β, β_1, β_2 etc.

The second assumption states, that the data sample must be randomly selected from the data population. Random selection ensure that (X_1, X_2,…,X_k,Y_i), i=1,…n are independently and identically distributed. This allows me to project my sample conclusions to the entire data. My data sample include all transactions that fulfilled the requirements, which are listed in the data section of this thesis. Although some transactions had to be excluded by one or more reasons I believe that my data sample is representative for the data population. Thus, I should not have any problems related to this.

The third assumption states no perfect collinearity, here it is important to note that collinearity is allowed, but not perfect or close to perfect collinearity. There are two parts to this, firstly none of the independent variables in the regression can be constant. If an independent variable is constant it still influences the estimators, but it will not add any value, because it does not explain anything about the dependent variable. Secondly, there cannot be any perfect or high correlation[2] between two independent variables. Often this becomes a problem in multiple regression analysis when one uses many independent variable to explain the same thing. E.g. gross margin, EBITDA margin and profit margin are often highly correlated and can therefore not be included together as independent variables in a regression analysis.

The fourth assumption of zero conditional mean states, that the error term "u" must have an expected value of zero. This is the key assumption, that makes the OLS regression unbiased (Stock & Watson, 2015). In the time series regression part I explained, that each error term cannot be correlated with any of the independent variable, this is also true for cross-sectional regression. When this assumption holds, the data is said to be exogenous. For my data sample to be exogenous I need to include as many relevant explanatory/independent variables as possible. Excluding explanatory variables lead to omitted variable bias, which is reflected in the error term. Issues related to zero conditional mean can be avoided by careful selection of variables. However, since it is impossible to collect all explanatory data I will have to be careful when selecting, what variables, I include in my regressions.

[2] High correlation is defined as a correlation coefficient higher than +-0.8.

The fifth assumption states, that there can be no changes in the variance of the error term in the regression function. Like the case with time series regression heteroscedasticity does not bias the estimators. Only their standard deviations are affected. However, in this part I care about the standard errors because they are used to construct the confidence intervals and t-statistics. The only way to know for sure if the model suffers for heteroscedasticity, is by testing. One possible test is the Breusch-Pagan test (BP test). Another way to avoid the heteroscedasticity problem is to apply HAC (Heteroscedastic- and Autocorrelative-Consistent) standard errors in the regression. I use a Breusch-Pagan test, to test my models for heteroscedasticity. If the null hypothesis of homoscedasticity is accepted (p-value above 0.05) then I use normal standard errors when running my regressions. If I am not able to reject heteroscedasticity, I first plot the residuals, and if they look heteroscedastic i will apply HAC standard errors in my regressions.

Lastly, the sixth assumption of large outliers comes from assuming that $X_1,X_2,\ldots,X_k$ and Y_i have nonzero finite fourth moments, i.e. that the dependent variable and regressors have finite kurtosis (Stock & Watson, 2015). OLS estimators of coefficients can in multiple regression models be sensitive to large outliers. To avoid problems from outliers I will plot the variable and check for outliers and if any unusual large outliers are detected I will check, if they are a data mistake or correct. If they are not at data mistake I will test how much they impact the model and potentially exclude them.

5 Data

In the next section of this thesis the data population will be defined along with the sample selection criteria. The data section is intended to connect the methodology section with the analysis and empirical results parts that follow next in section six.

5.1 Introduction

As defined in the research question the focus of this thesis is to study, if M&A is value creating in Western Europe. The relevant data is therefore samples from all countries within this region. To obtain a large enough data sample, I have included all transactions announced within the 5-year window of 1/1-2014 to 31/12-2018. To get an overview of the M&A market I have used the database

"Zephyr", which is available through CBS library. Zephyr is a very detailed and comprehensive database, that includes information about completed, announced and even rumored transactions. To obtain a complete dataset, with data for as many transactions as possible. I have used data from Bloomberg and Yahoo Finance to complement the dataset from Zephyr. Based on previous research and available data I have created a two-step list of requirements for transactions to be included in my sample. These will be discussed in the following part.

5.2 Data sample selection

The sample selection is divided into two parts. In the first part, that defines the gross sample all transactions from the Zephyr database, which can be used to answer the research question, is included. The second selection round ensures, that the final data sample fits the methodology presented in section 4.

5.2.1 First selection round

The first selection round criteria include the following requirements

1) Both bidder and target must be publicly listed at the time of announcement
2) Both bidder and target must be listed on a Western European stock exchange
3) The transaction must be announced between 1/1-2014 and 31/12-2018
4) The deal must be completed
5) The deal must be classified as a merger or an acquisition

First requirement, for me to be able to track the stock price development both bidder and target must be publicly traded at the time of the transaction. Tracking daily stock price enables me to calculate the daily stock returns in percentage. This makes it easy to compares value creation in different stocks markets, and I don't face any issues regarding different currencies. Total sample size: 101.799 deals.

Second, by requiring both the bidder and the target to be listed on Western European stock exchanges I ensure that my sample only contains companies within the geographical region, which I wish to research. By focusing on Western Europe I have a market, that is large enough to provide a sample, which is both sufficient in size and relatively new. Thus, I avoid depending on data, that is 20 years old and hard to obtain. Although there are differences between countries in Western Europe, all are recognized as highly developed, with relatively comparable cultures, legal systems, political stability and systems. The geographical definition of Western Europe i.e. which specific countries are included is determined by Zephyr. After this requirement, the potential sample is 34.678 deals.

Third, the transactions must be announced within the 5-year windows of 1/1-2014 and 31/12-2018. The 5-year span is selected to ensure a sufficient data sample, but also to avoid sample overlapping with previous papers. The M&A market has been booming during this period, driven by the favorable macroeconomic development, thus I expect a relatively even distribution of deals over the 5 years. M&As often come in waves with each wave having different characteristics on value and reasons (Alexandridis, Mavrovitis, & Travlos, 2011) and (Golbe & White, 1993). By only including a 5-year time window I can focus on, what drives M&A value in the present and conclusions can help decision makers of today and tomorrow. Adjusting for time-period the data sample shrinks to 3.889 deals.

Fourth, the transaction must be completed before it can be included. This requirement is in line with previous researchers (e.g. (Martynova & Renneboog, 2006), (Campa & Hernando, 2004) and (Alexandridis, Antypas, & Travlos, 2017)). Further, this thesis research value creation from M&A, which is most realistically measured from completed transactions. Further, data reliability is also strengthened by only included completed transactions, due to changes in stock prices (i.e. the abnormal returns) are more realistic in completed transactions compared to rumored, where volatility in stock prices can be higher. This requirement adjusts the data sample to 2.764 deals.

Fifth, this requirement is self-explanatory, since I can only analyze value creation in M&A by looking at M&A transactions. Further all transactions, in which ownership and control of a company is exchanged, are classified as either a merger or an acquisition. After the first round of selection I am left with a data sample of 448 deals.

5.2.2 Second selection round

To ensure the data sample fits the methodology, the second selection round set up a list of requirements, that the first-round data sample must fulfill to be included in the final data sample.

1) The stock price must be available for ~ 200 trading days prior to completion
2) The bidder is not allowed own more than 49.99% of the target before
3) The acquirer must be a majority owner, i.e. ownership of minimum 50.01%, after the transaction is completed

4) The stock must be traded at least 3 out of 4 days in the estimation period
5) No intracompany transactions are allowed
6) Financial information about the company prior to transaction must be available

First, to calculate the normal return using the market model I need the daily stock price developments for the entire estimation period described in the methodology section. By selecting a longer estimation period of 200 trading days I capture a normal daily return, where other external events do not have a large and lasting impact.

Second and third, I have decided that bidders cannot be majority shareholders in targets before the acquisition, meaning that bidders cannot hold more than 49,9% of the stocks before bid. Further after the transaction is completed the acquirer must be a majority shareholder, meaning owning at least 50,01% of the outstanding stocks. I exclude minority acquisitions, because they will have a lower impact on the stock price than majority acquisitions. Some companies have dual class shares: A and B. Both stock classes have the same right for cash flows, but they do not have the same voting power. This difference in voting power between share classes is reflecting in the share price of the A and B class, where shares with more voting power are priced higher than those with less. However, for this thesis. I do not account for dual share classes, and therefore assume that holding more than 50% of total stocks gives the same percentage of total votes. This assumption is reasonable, because I am looking at the market reaction, which considers the purchase price of the traded shares. Further both share classes have the same cash flow rights, and cash flows are what creates value for shareholders.

Fourth, this assumption is made to avoid problems from thin traded or illiquid shares. Illiquid shares are very often small companies. Fama & French (1992) argue in their now famous three-factor model, that the different size between bidder and target is one of the factors determining the abnormal return. The covariance between small illiquid companies and the market is close to zero, which results is a beta close to zero. A beta of zero does not represent the risk profile of a specific company. Further illiquid shares would yield an expected normal return close to zero, when in fact the return is higher but not recorded in the share price, because the shares are not traded. This would result in observed abnormal returns being overestimated, which would bias the results of this thesis. Previous researchers have come up with different ways to overcome the issue of thin trading. Scholes & Williams (1977) and Dimson (1979) both acknowledged, that betas from thin traded shares are biased and inconsistent. They have also presented method to calculate a more reliable beta. This model account for nonsynchronous trading and uses "*convenient consistent estimators*" to calculate betas. Dimson (1979) concludes that "*when non-trading is a problem, it is unlikely that empirical evidence will enable us to determine the ideal estimation method*". Later Cowan & Sergeant (1996 tested the Scholes and Williams method and concluded that "*There is no noticeable improvement in the power of the tests using Scholes-Williams betas. For some tests at some abnormal return levels, the power is greater, while for other combinations, it is lower or unchanged. Thus, for exchange-listed stocks, there is no apparent advantage to use the Scholes-Williams betas*". Thereby deem the method unreliable, same conclusion is reached by Brown & Warner (1985) and Dyckman, Philbrick, & Stephan (1984). Since financial researchers do not seem to be able to find common ground on how to solve the issue, I have decided to exclude the thinly traded stocks from my analysis as thin trading lead to a beta of zero which yield an expected normal return of zero, thus actual return equal abnormal return. Such assumption is not correct because the risk profile for that company is incorrectly estimated when beta equal zero. As no definition of "thinly traded" has been established, I have decided to exclude stocks, that have not been traded in one-in-four (1/4) days of the estimation period i.e. stock must be traded in at least 75% of the days in the estimation period[3]. The one in four is my own estimate, and is chosen because beta reliability increases in trading volumes. By using a high estimate trading requirement like three out of four days I improve the date quality.

Fifth, the analysis excludes all intracompany transactions. The reason for excluding intracompany transactions is, that they do not show realistic premiums as the transaction price i.e. purchase price is often based on an average of the price for the last months. Which is a lower price, than what is observed for non-intracompany transactions.

Sixth, to conduct the cross-sectional regression analysis, I need financial information on bidders and targets. This requirement is only related to the cross-sectional regression analysis, i.e. if the needed financial data is not available, the transactions is still be included in the event study but it is excluded from the second part of the analysis. After considering all the data requirements from both selection round I have a final sample consisting of 189 bidders and 142 targets across a total of 202 deals. 129 deals include matching bidder and target, while 73 deals only include either the bidder or the target.

[3] A stock is considered traded, when trading volume is above 0. Thus, daily return can still be 0.00% if the closing price is the same as the day before.

The reason for mismatch between number of bidders and targets is due to more smaller targets are thinly traded and thereby excluded from the sample. Appendix 1 include a list of all bidders and targets included in the final data sample.

5.3 Descriptive statistics

The next part will take a deeper look at the final data sample. In the first-round I will look at the sample characteristics and summary statistics from the first round of data requirements, and in the second-round I will look at data characteristics from the second data selection round.

5.3.1 First-round data characteristics

From the first round of data collection it is especially interesting to look at, how the sample is spread across time and geography. First, my sample span across a relatively short period of time equal to five years. Some previous researchers have used longer periods, where the year by year number of deals differs significantly and often appears in a wave pattern. However, since my period is relatively short and is not impacted by any major financial crises, I expect a relatively even distribution of deals over the five-year period.

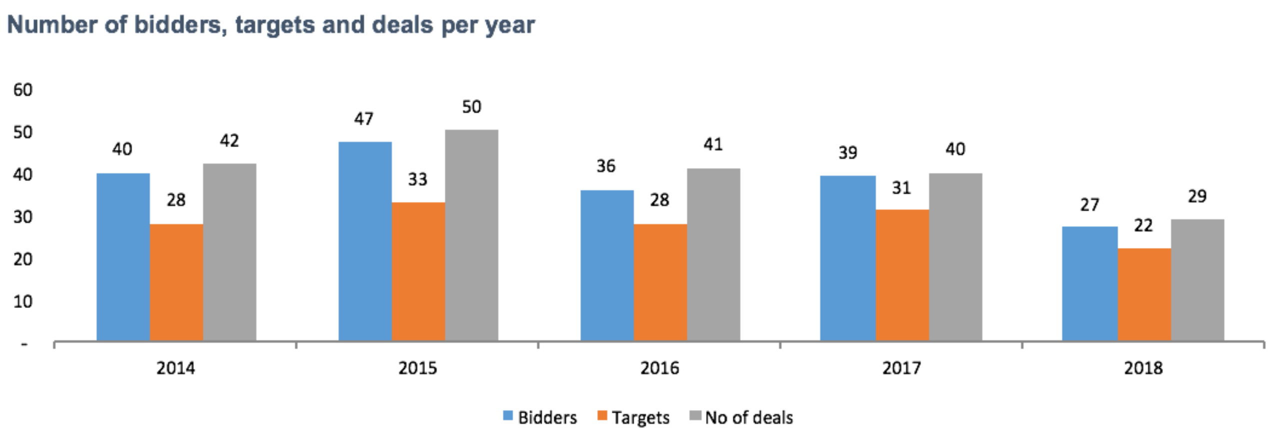


Figure 2: number of bidders, targets and deals in per year

Figure 2 presents the distribution of bidders and targets per year as well as the total number of deals that year. E.g. in 2014 there were 42 deals, of which I have data on bidders for 40 of them and data on the targets in 28 of the deals. My prediction of an evenly distribution of deals over the five years is not completely wrong. 2014 to 2017 all had relatively even numbers of deals between 41 and 50, although 2018 is falling a bit behind with only 29 deals. One possible reason for the lower activity in

2018 is Brexit, and the volatile political environment surrounding the exit talks between the British government and the EU. Another important observation from figure 2 is the data consistency. For all five years, the number of bidders and targets available is approximately the same proportion to the total number deals, which suggest that my sample is representative for the entire five-year period. Second, the geographical distribution of bidders and targets is presented in figure 3.

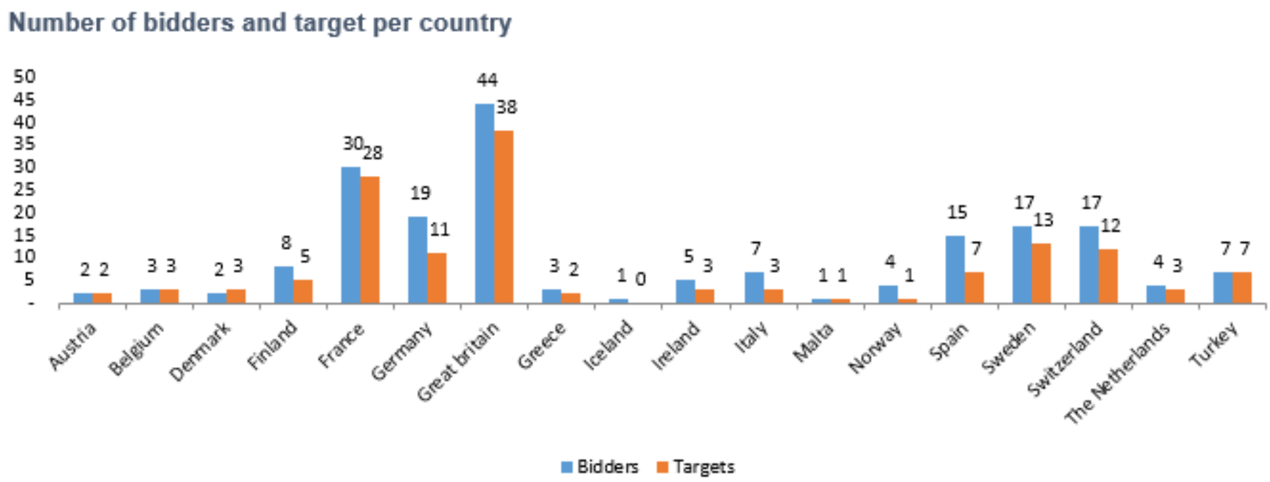


Figure 3 distribution of bidders and targets per country

From figure 3 I observe that the number of bidders and targets from each country match very well. As expected it is the larger countries like Great Britain, Germany and France, that have the most sample companies. A small surprise is Sweden, Finland and Switzerland, which also have a lot of companies included, relative to country sizes, while Italy and the Netherlands have less than I expected based on the size of those countries. The similar distribution of bidders and targets by country could indicate many domestic rather than cross border deals. Of the total 202 deals, 134 (66.34%) are domestic deals and 68 (33.66%) are cross border deals. Further I note 160 of the 189 bidders and 122 of the 142 targets are from EU. The proportions of domestic and cross-border deals between EU and non-EU countries are approximately the same.

5.3.2 Second-round data characteristics

In the second-round I will look at other characteristics of the final sample, such as: method of payment, focused or diversifying M&A strategies, cash flows, market capitalization, deal size and in the end, look at some of the characteristics of bidder and target CAR.

	Number of Bidders	Number of Targets	Number of Deals
Cash	66	53	73
Stocks	41	35	46
Mixed	63	53	64
Unknown	19	1	19
Total	**189**	**142**	**202**
Focused	111	81	115
Diversifying	78	61	87
Total	**189**	**142**	**202**
Manufacturing	50	36	n.a.
Trans. Comm. & Utilities	20	11	n.a.
Retail & Wholesale	11	14	n.a.
Finance	58	31	n.a.
Services	33	39	n.a.
Other	17	11	n.a.
Total	**189**	**142**	**202**

Source: Bloomberg, Zephyr

Table 1: Distribution of payment methods, strategy and industry classification for bidders, targets and total number of deals

Looking at table 1 I see cash is the most popular method of payment with 73 deals using cash, while stocks are the least popular with only 46 deals. 64 deals use a mix of both stock and cash while 19 deals have an unknown method of payment. For the underlying strategy or rationale behind the transaction I find, that most bidders choose to invest in targets, that operate within the same overall industry with 115 deals being classified as focused and 87 as diversifying.

Because most the sample deals are focused i.e. intra-industry, I would expect to see relatively even proportions of bidder and target companies within each industry category. Table 1 presents bidder and target industry distribution, with the financial sector being the one with the most bidders, and the service industry being the one with the most targets. Manufacturing comes in second place for both bidders and targets. When looking at which industries are keener to make acquisitions, and which are popular targets, I find it worth noticing that the retail & wholesale and services industries have been targeted more times, than they have made acquisition on their own. While the low activity in the retail & wholesale industry can be explained by the struggles the industry have seen lately, especially retail stores are losing business to internet giants (Townsend, Surane, Orr, & Cannon, 2017). The service industry includes technology and software, which are business areas, that are growing and attractive (The Boston Consulting Group, 2017).

	Mean	Std. Dev.	Median	Min	Max	K
Bidder Cash Flow	686.89	3,852.88	35.90	-7,431.30	43,189.00	168
Target Cash Flow	15.96	543.17	4.80	-3,551.00	2,407.70	123
Bidder Mcap	8,757.60	20,330.42	1,321.29	0.73	116,439.25	186
Target Mcap	2,606.50	6,214.31	398.50	1.89	39,034.54	100
Bidder beta	0.596	0.544	0.546	-1.947	5.034	189
Target beta	0.530	0.428	0.516	-0.918	1.849	142
Deal size	1,950.01	5,656.27	240.04	0.27	50,814.93	182

Cash flows, market capitalization and deal size denoted in EUR in millions

Source: Bloomberg, Zephyr

Table 2: Summary statistics for cash flows, market capitalizations, betas and deal sizes

Table 2 presents the summary statistics for bidder and target cash flows, betas, market capitalizations and deal sizes. Most noticeable is the size difference between the average bidder and target. This is especially true when looking at cash flows. Both bidder and target cash flow summary statistics are heavily affected by large observation, which pulls the mean far above the median value. The fact that the data is dispersed, is also clear when looking at the standard deviation, which is five times the mean for bidders, and more than 30 times larger for targets, this can cause problems for generating high t-statistics in the analysis part. The extreme maximum and minimum values for cash flows are recorded for financial institutions, which often have extreme variations in cash flows. The size difference between bidders and targets is more modest when looking at the market capitalization. However, the mean is still much higher than the median, which causes the standard deviation to increase. The fact the smallest bidder is half the size of the smallest target, is most likely a fault in the data, because data was not available for all targets and bidders. The dynamics of bidder and target betas are relatively even. Both have, compared to expected market beta of one, low average betas of 0.596 and 0.530 respectively. The difference in minimum and maximum and the higher standard deviation suggest the bidders and targets are well dispersed between high and low beta industries.

MM-CAR in %	Mean	Std. Dev.	Median	Min	Max	K
Bidder +-1 Day CAR	-0.25%	5.99%	-0.30%	-17.82%	28.89%	189
Bidder +-2 Days CAR	-0.54%	6.66%	-0.11%	-22.14%	24.48%	189
Bidder +-5 Days CAR	-0.83%	8.16%	-0.53%	-29.74%	25.38%	189
Bidder +-10 Days CAR	-1.24%	11.59%	-0.43%	-54.45%	33.31%	189
Target +-1 Day CAR	11.49%	17.62%	6.47%	-41.81%	70.14%	142
Target +-2 Days CAR	12.65%	18.70%	8.04%	-54.66%	70.79%	142
Target +-5 Days CAR	12.63%	21.04%	9.78%	-60.01%	91.09%	142
Target +-10 Days CAR	13.68%	21.86%	10.76%	-60.99%	86.99%	142

Source: own calculation

Table 3: Summary statistics for CAR, calculated using the market model method

Table 3 above presents the summary statistics for both bidders' and targets' CAR. Most noticeable is the difference in the mean CAR (i.e. CAAR) between bidders and targets. This difference suggests targets receive all the value creation from M&A, while bidders on average lose value. The standard deviation is still large, suggesting a dispersed dataset. The median is not far from the mean values, which indicate the extreme values, which increases the standard deviation are observed in both ends of the distribution. The most extreme values are recorded from targets, which also was expected. The fact that the mean value for all four event windows are relatively even, suggest shareholder value is created on or very close to the announcement day. The findings above lead me to expect large positive and statistical significant CAAR for targets, while bidder abnormal results are expected to be approximately zero. The CAR is calculated using the market model explained in the methodology section. Appendix 2 includes a list over the national stock indexed used as proxy for the market.

6 Analysis and empirical results

In the next section of this thesis I present the empirical analysis and its results. The first part of this section will be the event study to investigate if abnormal returns are present and statistically significant. The second part is the cross-sectional regression analysis, that investigate the value drivers behind the value creation from M&A activities.

6.1 Value creation in M&A

In this part of the thesis I test the short-term value creation from M&A activities to bidder and target shareholders. It is important to clearly separate bidders and target, which is why hypothesis 1.1 and 1.2 has been formulated separately. The results from those two hypotheses form the core of the results used to answer the research question. In hypothesis 1.1 I use a two-sided t-test to test, whether the stock price react positively or negatively to M&A activities for bidding companies. In hypothesis 1.2 I use the same two-sided t-test to test the stock price reaction for targets. As stated in the methodology section, this is done by using an event study, for which I have formulated several event windows. Having several event windows enables me to do sensitive analysis, robustness checks and assume a weaker form of market efficiency. The value creation is also tested using a non-parametric rank test, which considers that abnormal returns are often not normally distributed, but rather have “fat-tails” and be t-distributed, characteristics my abnormal returns show. The distributions of bidder and target abnormal returns are plotted in appendix 3. For both bidders and targets I have calculated CAR using both the market model and the constant-mean-return model. As explained in the methodology section the market model results will form the basis, for whether I accept or reject hypotheses 1.1 and 1.2, where the constant-mean-return model is more used as a sensitivity analysis and robustness check.

6.1.1 Hypothesis 1.1

The literature review outlined the previous findings on bidder announcement returns. No consensus was found, since researchers disagreed whether M&A is value creating for bidding firm or not. Most found zero announcement returns, like Campa & Hernando (2004), Eckbo & Thorburn (2000) and Bruner (2002). While others found small and positive abnormal returns like Alexandridis, Petmezas, & Travlos (2010), Martynova & Renneboog (2011) and Goergen & Renneboog (2004) did. Or small and negative abnormal returns like Hazelkorn, Zenner, & Shivdasani (2004) and Mulherin & Boone (2000). They all agreed that M&A had certain advantages such as synergies, cost-savings and new markets. But they also had disadvantages such as risks, foreign cultures, new competitors. Based on these findings I formulated hypothesis 1.1 as:

Hypothesis 1.1: Bidder abnormal return is zero in the event window

To test the above hypothesis 1.1, I have performed an event study with several event windows. The results obtained from my event study are then tested for statistical significance using a t-test and rank test. The t-test will yield a numerical result, that indicates the actual abnormal return to shareholders from M&A activities. The rank test will merely state, whether abnormal returns are present and if these are statistically significant. For both the t-test and the rank test I have formulated the following event windows: -1, +1 day, -2,+2 days, -5,+5 days and -10,+10 days. For the t-test I have also looked at event windows covering the period before and after the announcement day. These include -10,-1 day -10,0 days, +1,+10 days and 0,+10 days, where 0 equal the announcement day. The results and interpretations of the two tests follow below.

Parametric t-test – Market model

I begin with the parametric t-test, which presents the actual return to bidder shareholders. I tested CAR, which when taken as an average for all bidders become CAAR.

	-10,+10	**-5,+5**	**-2,+2**	**-1,+1**	**-10,-1**	**+1,+10**	**-10,0**	**0,+10**
CAAR	-1.24%	-0.83%	-0.54%	-0.25%	-0.03%	-1.37%	0.13%	-1.21%
Std. Dev.	11.56%	8.14%	6.64%	5.97%	6.88%	7.86%	7.98%	8.45%
t-stat	-1.47	-1.40	-1.11	-0.58	-0.05	-2.40**	0.23	-1.97*
p-value	0.142	0.163	0.270	0.559	0.955	0.018	0.822	0.050
K	189	189	189	189	189	189	189	189

****,**,* indicate significance level for 1%, 5%, 10%*
Source: own calculations

Table 4: Parametric test results for hypothesis 1.1 with market model bidder CAAR

Table 4 presents the results from the parametric t-test for the cumulative average abnormal returns of bidders. The dependent variable is CAR. The t-test was performed as a two-sided test, which tests for both negative and positive abnormal return from M&A. As seen in table 4 all the coefficients from the first four event windows are negative, small and statistically insignificant, as indicated by the t-stat and p-value. Further, the abnormal returns are decreasing as the event window is extended, which signals that AAR in the event window is evenly distributed and not centered around the announcement day. Looking at the last four event windows in table 4, I find the period after the announcement day have small, negative and statistically significant, at the 5% and 10% level, abnormal returns of -1.37% when excluding the announcement day, and -1.21% when including the announcement day. Suggesting this period is value destroying to bidder shareholders. The period prior to announcement have results, that are close to zero and statistically insignificant.

Table 5 below presents the daily AAR for bidders for the entire event window and the corresponding t-statistics.

Days	AAR	t-stat	P-value	K
-10	-0.18%	-1.1485	0.2522	189
-9	0.02%	0.0810	0.9356	189
-8	-0.07%	-0.4377	0.6621	189
-7	0.36%	2.0548**	0.0413	189
-6	0.03%	0.1293	0.8973	189
-5	-0.05%	-0.3555	0.7226	189
-4	-0.04%	-0.2313	0.8173	189
-3	-0.04%	-0.2543	0.7995	189
-2	-0.11%	-0.7259	0.4688	189
-1	0.05%	0.3922	0.6954	189
0	0.16%	0.5552	0.5794	189
+1	-0.47%	-1.6413	0.1024	189
+2	-0.18%	-1.2156	0.2257	189
+3	-0.05%	-0.2847	0.7762	189
+4	-0.06%	-0.3844	0.7011	189
+5	-0.06%	-0.3947	0.6935	189
+6	-0.08%	-0.4634	0.6436	189
+7	0.03%	0.2374	0.8126	189
+8	-0.02%	-0.1287	0.8977	189
+9	-0.24%	-1.8094*	0.0720	189
+10	-0.26%	-2.1903**	0.0297	189

****,**,* indicate significance level of 1%, 5%, 10%*

Source: Own calculations

Table 5: Parametric test results for bidder daily AAR

I find three of the twenty-one days in the event window have abnormal returns which are statistically significant (-7, +9, +10). The results from of +9 and +10 help explain the results of negative abnormal return in the period after announcement seen in table 4. However, since these three days are relatively distant from the announcement date, I cannot exclude the possibility that other external events are the reason the for results. The day zero announcement effect is 0.16% but statistically insignificant, suggesting no short-term value creation to bidder shareholders from M&A activities. Further, the relatively even distribution of abnormal returns throughout the event window makes it hard to conclude anything about market efficiency. The late effect from +9 and +10 indicate a lower level of market efficiency, but it is not concluding.

Figure 4 visualizes the results from table 5. The daily AAR is projected on the left axis and the t-statistics on the right. Here the most noticeable effect is the decrease from day zero to day one from 0.16% to -0.47%. However, since this effect is not statistically significant I cannot draw any conclusions. The correlation between AAR and the t-statistics is due to the standard deviation being constant, and the t-statistics therefore heavily depend on the AAR. Day +9 does not seem significant in figure 5, which is due to the projected critical level is the 5% level.

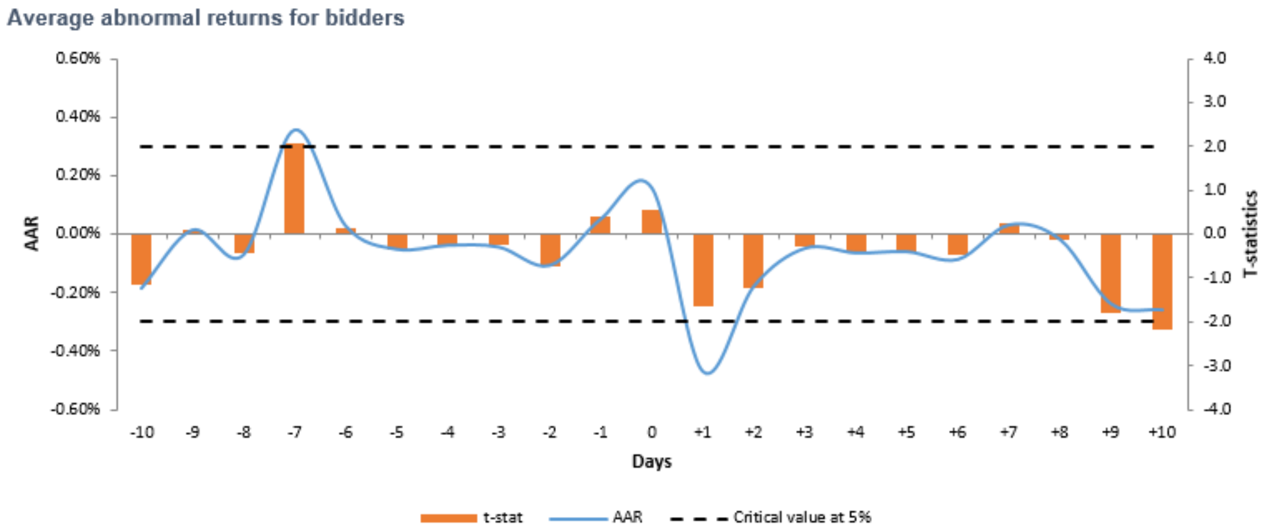


Figure 4: Daily AAR graphed with t-statistics and 5% significance level band.

The day to day accumulation effect throughout the event window is presented in figure 5 below, where the AAR is indexed at 100 at day -10.

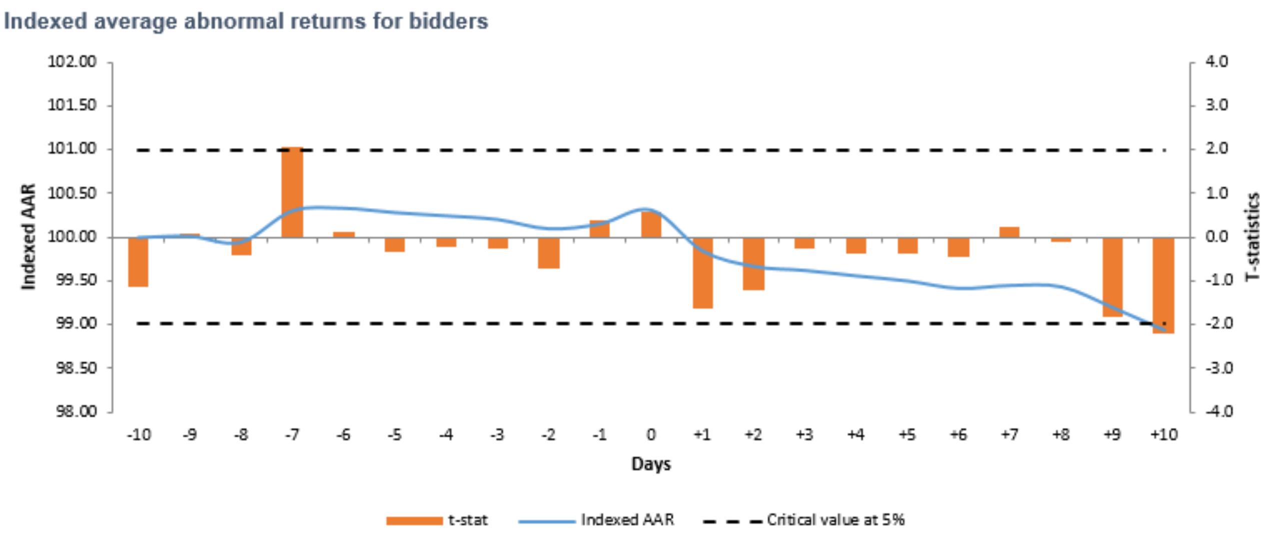


Figure 5: Indexed AAR showing the accumulating effect throughout the event window

The t-statistics and the critical value bands are the same as in figure 4 above, because the accumulated result cannot be tested for significance. They are merely included to guide and explain the direction of the indexed AAR. The indexed AAR presents the same negative trend in the period after announcement, which was discussed above.

Constant-mean-return model

To test the sensitivity of the results above I have calculated CAAR using the constant-mean-return model (Henceforth: CMRM) and used the same t-test as above.

CMRM - bidders	-10,+10	-5,+5	-2,+2	-1,+1
CAAR	-2.23%	-1.25%	-0.59%	-0.18%
Std. Dev	14.25%	8.79%	6.82%	6.08%
t-stat	-2.1477**	-1.9533*	-1.1958	-0.4104
p-value	0.0330	0.0523	0.2333	0.6820
K	189	189	189	189

****,**,* indicate significance level of 1%, 5%, 10%*

Source: own calculations

Table 6: Parametric test results for Constant-Mean-Return Model bidder CAAR

Table 6 presents the results from the t-test of the CAARs calculated using the CMRM method. Comparing the results to those obtained from the market model, I find all event windows results in negative returns to bidder shareholders, and that CAAR for -10,+10, -5,+5 and -2,+2 are lower when using CMRM, while the -1,+1 event window yields an abnormal return that is slightly higher of -0.18% compared to -0.25%. Further and more important I find the CAAR for -10,+10 and -5,+5 event windows are statistically significant at the 5% and 10% level. The fact the statistically significant results only appear in the two longest event windows, and not in the shortest, could suggest the abnormal returns are not a direct effect of the transaction, but rather, an effect from an external event.

The results from the CMRM seems to be more extreme than those of the market model. This is also seen by looking at the standard deviation, which is higher for the CMRM method.

Non-parametric Rank test

The rank test proves that abnormal returns are present, if the event window average is above 50% and is statistically significant at the same time. The results are presented in table 7.

	-10,+10	-5,+5	-2,+2	-1,+1
Event window avg.	49.41%	49.24%	48.80%	49.52%
Std. Dev	5.86%	8.59%	13.91%	18.26%
Days in event window	21	11	5	3
t-stat	-0.46	-0.29	-0.19	-0.05
p-value	0.323	0.385	0.424	0.482
Degrees of freedom	188	188	188	188

****,**,* indicate significance level of 1%, 5%, 10%*

Source: own calculations

Table 7: Non-parametric Rank test results for bidders

As seen in table 7, the event window average never crosses above 50% for any of the four event windows, and the results are not statistically significant. The rank test confirms the results from the t-test in the previous part. The increasing standard deviation is due to many extreme value at the announcement date, due to some bidders have large positive abnormal returns, and some have large negative abnormal returns on the announcement day.

Conclusion

The results from the parametric and non-parametric tests suggest bidders earn negative abnormal return from M&A activities, however those results are statistically insignificant. Only the CMRM CAAR yield a significant result in the two longest event windows, but not in the two shortest ones, which indicate the statistically significant abnormal returns are not due to the transaction. This is supported by the AAR results, which indicate no value creation happens in the event windows centered around the announcement day, because all coefficients are small and insignificant. In the period after announcement the t-test indicate, that bidders lose value, and this effect is statistically significant. The reason behind the value destruction in the period after announcement is due to negative average abnormal return on day +9 and +10. However, since these days are relatively long after the announcement date, I cannot rule out the possibility of these negative returns are due to other events. The results for the period prior to the announcement data are close to zero and insignificant. The rank test results confirm the results from the t-test of no positive abnormal returns to bidding shareholders. The results indicate the average abnormal return in the event window is smaller than the average abnormal return earned in the estimation period. It seems that the risks from M&A outweigh or equals the rewards of possible synergy effects. The insignificant results of the AAR in the days close to the announcement day makes it hard to conclude on market efficiency.

Based on the results I can confirm hypothesis 1.1 of zero abnormal return to bidders' shareholders in the event window. The results from my analysis are in line with those of Campa & Hernando (2004), who studied a European sample from 1998 to 2000, and Eckbo & Thorburn (2000), who studied a sample consisting of Canadian and American firms. Further the findings are supported by Bruner (2002) and Franks, Harris, & Mayer (1988). It is worth mentioning that my results contradict those of Martynova & Renneboog (2011). They found positive abnormal returns to European bidders in the 1990s. They mentioned the private status of targets (i.e. not publicly listed) as a characteristic, that increases value creation for bidders. The private status of targets make my results less comparable to theirs, and I therefore find the conclusions of Campa & Hernando (2004) more comparable to mine.

6.1.2 Hypothesis 1.2

Opposite to the bidder abnormal return, the literature review described how previous researchers all agreed, that targets earn positive and statistically significant returns, when they engage in M&A activities. Mostly, previous researchers found very large abnormal returns to targets. Bradley, Desai, & Kim (1988) found targets earn an average of 32% in abnormal returns, while Alexandridis, Antypas, & Travlos (2017) found 29.32%. Others like Campa & Hernando (2004) found more modest target abnormal return of 9%. The previous results lead me formulate hypothesis 1.2 as

Hypothesis 1.2: Target abnormal return is positive in the event window

In the summary statistics in the data part of this thesis, I formulated my expectation to find positive and statistical significant target abnormal return. The average CAAR was around 10-15% which is not as high, as what is reported by some of the previous researchers in the literature review, but still a good return for target shareholders. As with hypothesis 1.1 I will test hypothesis 1.2 with a t-test and a rank test, where the t-test again will yield an actual coefficient for abnormal returns, and the rank test will merely state whether the average abnormal return in the event window is larger than the average abnormal return in the estimation period. The event windows I have selected for testing is the same as those selected for bidder abnormal returns in hypothesis 1.1. The results and interpretations from the t-test and rank test follow below.

Parametric t-test

Table 8 presents the results from the t-test performed for CAAR for targets in all eight event windows. The t-test is two-sided test, which tests for both positive and negative abnormal returns.

	-10,+10	-5,+5	-2,+2	-1,+1	-10,-1	+1,+10	-10,0	0,+10
CAAR	13.68%	12.63%	12.65%	11.49%	2.62%	1.96%	11.72%	11.06%
Std. Dev.	21.78%	20.96%	18.63%	17.56%	11.19%	13.42%	18.69%	18.31%
t-stat	7.46***	7.16***	8.06***	7.77***	2.78***	1.74*	7.44***	7.17***
p-value	0.000	0.000	0.000	0.000	0.006	0.085	0.000	0.000
K	142	142	142	142	142	142	142	142

****,**,* indicate significance level for 1%, 5%, 10%*

Source: own calculations

Table 8: Parametric test results for market model target CAAR

From table 8 I find the CAAR for targets in the first four event windows to be large, positive and statistical significant at the 1% level. The CAAR seem stable from 11.49% in -1,+1 to 13.68% in -10,+10, which suggest most value is created on or very close to the announcement day. The last four event windows look at value creation in the period prior and after the announcement date. I find the period prior to announcement yield 2.62% in CAAR, and that is statistically significant at 1%, while the period after announcement yield 1.96% CAAR and is statistically significant at 10%. When including the announcement day, the CAAR spike to 11.72% and 11.06%, both significant at 1%. Those results suggest shareholder value is created on the announcement day and indicate a high level of market efficiency.

Table 9 below presents the daily AAR for targets along with the t-statistics for each day in the event window. From table 9 I observe five days have statistically significant AAR (-9, -2, -1, 0 and +1). Table 8 indicated that shareholder value is created on or close to the announcement day, because all four event windows had relatively even abnormal returns. Table 9 confirms this is true the announcement date yield on average for target abnormal returns equal to 9.10%. The day -9 seems odd, and since it is relatively far away from the announcement data I cannot rule out the possibility, that the return on that day is due to another external event. The significant AARs at day -2 and -1 suggest some investors knew, that the company was about to be acquired. Thereby trading on insider information, however, this is a topic for the following discussion in section seven. The AAR at day +1 looks like a correction to the announcement day returns.

Days	AAR	t-stat	P-value	K
-10	0.27%	1.5287	0.1286	142
-9	0.72%	2.5497**	0.0119	142
-8	-0.04%	-0.20647	0.8367	142
-7	0.06%	0.37965	0.7048	142
-6	0.30%	0.98779	0.3249	142
-5	0.13%	0.58109	0.5621	142
-4	-0.32%	-1.2543	0.2118	142
-3	0.03%	0.09814	0.9220	142
-2	0.81%	2.5547**	0.0117	142
-1	0.64%	2.4797**	0.0143	142
0	9.10%	7.3472***	0.0000	142
+1	1.75%	1.8495*	0.0665	142
+2	0.35%	1.078	0.2829	142
+3	-0.03%	-0.16055	0.8727	142
+4	0.04%	0.14056	0.8884	142
+5	0.14%	0.81734	0.4151	142
+6	-0.07%	-0.51553	0.6070	142
+7	-0.26%	-1.4592	0.1467	142
+8	0.02%	0.10894	0.9134	142
+9	-0.01%	-0.060009	0.9522	142
+10	0.04%	0.24373	0.8078	142

****,**,* indicate significance level of 1%, 5%, 10%*

Source: Own calculations

Table 9: Parametric test results for target daily AAR

Figure 6 visualizes the AAR findings from table 9. Since the standard deviation is the same for all days in the event window the t-statistics should be highly correlated with the daily AAR. Although this is not as clear here, as it was with case of bidders in figure 5.

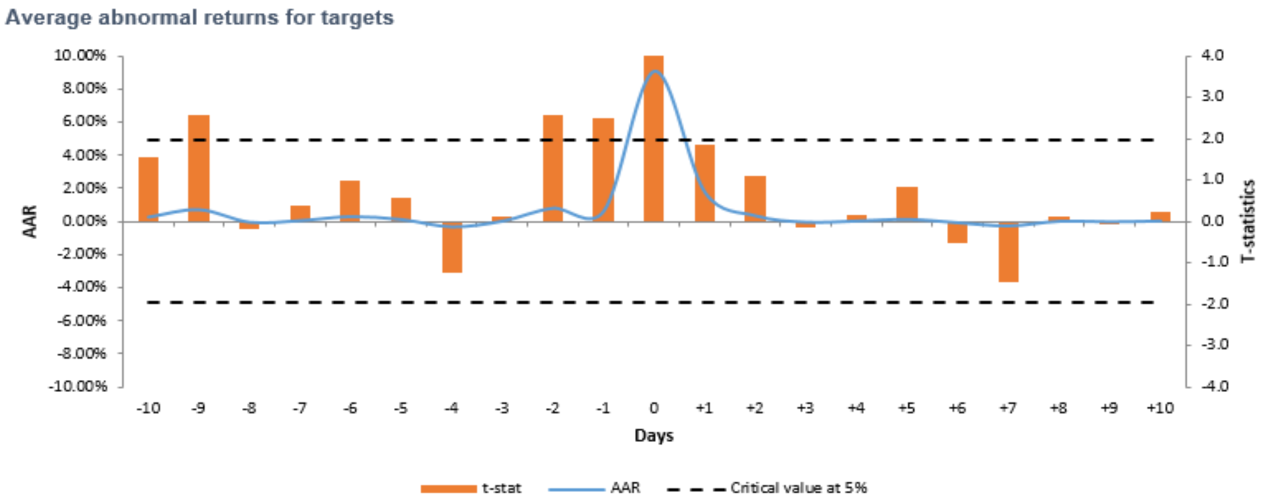


Figure 6: Daily AAR graphed with t-statistics and 5% significance level band.

As expected from table 9 the AAR have a large spike on the announcement day in figure 6. Since the announcement day AAR is so high it makes the AAR of all other days in the event window seem small. This is due to the right-side axis span is modelled from -10% to +10%, where the figure 5 for bidders only went from -0.6% to +0.6%. The fact most of the abnormal returns are created on the announcement day, indicate the stock markets are very efficient in absorbing information, and incorporate it into the stock prices, and maybe a bit too efficient on day -2 and -1. Since the announcement day return for bidders was only 0.16% and insignificant, it seems like 100% of the value creation from M&A will go to target shareholders. One reason, why the bidding shareholders do not receive any abnormal return, could be due to the difficulty of valuing synergy effects. Most the of the announcement day abnormal return for target comes from the premium offered by the bidding firm. A premium is what the bidder offers to pay more than the current market valuation. This could indicate bidders are paying too much for the control of the targets. On the contrast if the shareholders of the bidding company thought the premium offered was too high, they would react, which would most likely result in decreasing bidder stock price or the transaction being stopped. Since such negative abnormal returns for bidders is not found in my analysis, it seems like the premium offered is equal to the value of the synergies, that the acquisition is expected to produce, thereby keeping the value of the bidding firm constant.

To visualize the accumulated effect of AAR for target figure 7 below presents the indexed daily AAR. The indexed AAR show the large value creation on the announcement day. It also shows the period prior to and after the announcement day are relatively stable, which again suggests a high level of market efficiency. Only day -2 and -1 give a small upward bump in the index. The index from day +2 until +10 is stable suggesting all value creation has already happened.

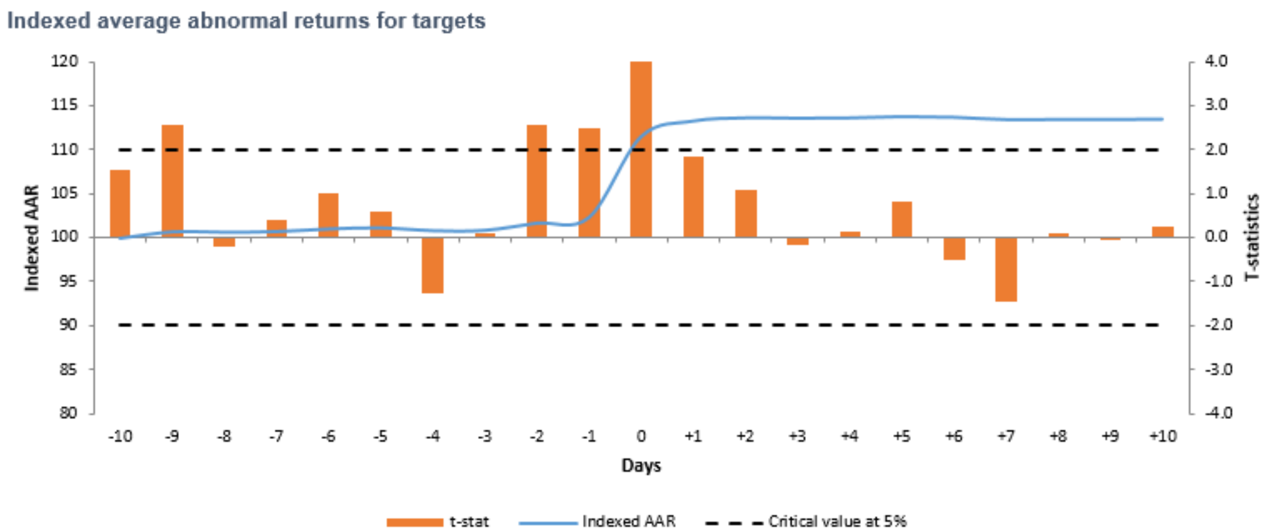


Figure 7: Indexed AAR showing the accumulating effect throughout the event window

Constant-mean-return model

Table 10 present the results of testing CAAR calculated using the CMRM.

CMRM - targets	-10,+10	-5,+5	-2,+2	-1,+1
CAAR	11.07%	9.59%	8.80%	7.88%
Std. Dev	23.89%	23.01%	18.55%	17.57%
t-stat	6.1038***	5.9146***	8.0159***	7.7358***
p-value	0.0000	0.0000	0.0000	0.0000
K	142	142	142	142

****,**,* indicate significance level of 1%, 5%, 10%*

Source: own calculations

Table 10: Parametric test results for Constant-Mean-Return Model target CAAR

Comparing the CMRM results to those of the market model above I find that the market model produce higher and more stable results between 11.49% and 13.68%. The CMRM have lower and more dispersed CAARs, which result in higher standard deviations. The higher standard deviations for CMRM result in lower t-statistics. However, the results using CMRM are still statistically significant at the 1% level for all four event windows tested. The main difference between the market model and CMRM, is that the market model considers the general development in the stock market. The more volatile CAARs produced by the CMRM indicate the market development is an important factor, that provides stability to the abnormal returns. Further, as the market model increases target CAAR compared to the CMRM, it seems like the market has had a lower growth rate, compared to the target, at the time of the transactions. This comes from the abnormal return is equal the actual return minus the expected normal return. Therefore, the only way the market model can produce higher target CAAR than the CMRM, is by having a lower expected normal return. There are two factors, that can lower the expected normal return (i.e. increase abnormal return) for the market model: 1) the market development is negative in the event window, and 2) low target beta. If the market is decreasing in the event window, and if the target beta is positive, the expected normal return is negative, and thereby increasing abnormal return. If beta is low, then the market development impact is smaller, and thereby decreasing the expected return compared to high target beta. In my case I cannot say with certainty, which effect causes the market model to yield a lower expected normal return, and thus higher abnormal return than the CMRM. My sample of targets have an average beta of 0.53, which is low compared to expected average beta of 1 (i.e. market beta). From eq. 3 expected normal return is equal to:

$$R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it}$$

Therefore, when beta is low at 0.53, a high expected normal return depends on the market return being extremely high or a high alpha, which is often very close to zero. A negative market development in the event window would make the average expected normal return negative, and thus the abnormal return would be larger, when the average actual return is positive. Thus, I am unable to determine which effect is stronger, and thereby the main reason for the difference between the market model and the CMRM CAAR results.

Note: The CMRM also produces lower bidder CAAR in the three longest event windows. The reason behind the difference is the same as explained above. I merely chose to write the explanation here, because the difference for targets is larger than it is for bidders.

Non-parametric rank test

Table 11 display the results from the rank test on targets abnormal return. Since I am only interested in knowing, if abnormal return is positive, I am using a one-sided test for the p-values and t-statistics.

	-10,+10	-5,+5	-2,+2	-1,+1
Event window avg.	52.43%	53.71%	58.76%	61.57%
Std. Dev	5.91%	9.38%	13.14%	17.63%
Days in event window	21	11	5	3
t-stat	1.88**	1.31*	1.49*	1.14
p-value	0.031	0.096	0.069	0.129
Degrees of freedom	141	141	141	141

****,**,* indicate significance level of 1%, 5%, 10%*

Source: own calculations

Table 11: Non-parametric Rank test results for targets

The results of the rank test are very unanticipated, all four event windows have averages above 50%, but none of them have abnormal returns statistically significant at the 1% level. The -10,+10 indicate abnormal return significant at 5% while -5,+5 and -2,+2 indicate abnormal return at the 10% level. Table 11 shows the t-statistics are decreasing in the event window average, which seems odd. The reason behind this relationship is the standard deviation. The standard deviation is increasing, when the event window gets shorter. The increasing standard deviation in shorter event windows is due to extreme values at the announcement date. Targets often have large positive or large negative abnormal returns on the announcement day. These extreme values generate ranks close to zero or one, and thereby increasing the range of the data sample, which results in the larger standard deviation.

Conclusion

Both the market model and the CMRM produce results in favor a large and positive abnormal return to targets in M&A transactions. The market model produces the highest and most stable CAAR, while the CMRM produces lower and more dispersed CAAR across the four event windows. The AAR analysis indicate value is created on the announcement day and the days surrounding it, which again suggest a high level of market efficiency. Although day -2 and -1 also have statistical significant abnormal returns which, if connected to the transactions, would suggest insider trading, which I will discuss in section seven of this thesis. From the market model in table 8, I find both the period prior to and after the announcement are value creating. The CMRM method does not test those event windows, but the increased CAAR from -1,+1 to -10,10 indicate, that both periods contribute to increasing CAAR for targets. The difference between the market model and CMRM is due to differences in expected normal returns caused by two effects, negative market development in event windows or low target beta. From my analysis, I am unable to conclude which effect is the stronger one. The rank test concludes the abnormal return in the event windows are higher than the abnormal return in the estimation period. This result is statistically significant for -10,+10, -5,+5 and -2,+2 at the 5% and 10% level. The standard deviation is too high for the abnormal return in the -1,+1 event window to be significant.

Based on the results presented above, I accept hypothesis 1.2, and I conclude targets earn positive and statistical significant abnormal returns from M&A activities. The abnormal returns are robust across different event windows lengths and methods of calculation. The results are in line with those of previous researchers presented in the literature review. Specifically, I want to mention Campa & Hernando (2004), who found average target abnormal returns of 9%. Although their event window was one month long the results are not far from mine, and thus comparable.

6.2 Method of payment

The second part of the analysis section tests the value drivers behind M&A value creation, starting with the method of payment. Neoclassical theory depicts the method of payment should not have any impact on the market reaction, assuming stocks are accurately valued and all information is incorporated into the price. However, often theory and practice does not agree, which have been proved by previous researchers. Because of this, I research the impact from different methods of payment on bidder and target abnormal return. For each hypothesis, I run 8 regressions, four using the market model CAR and four using the CMRM CAR. I run four regression for each model, because I have four event windows and thus four different CARs.

6.2.1 Hypothesis 2.1 and 2.3

The literature review talked a great deal about the signaling effect, which theorize the use of stocks for payment signals to the market, that management sees the stock as being overvalued. Thus, management is incentivized to use the overvalued stock to acquire companies, instead of cash, because they expect long-term negative returns. Eckbo, Giammarino, & Heinkel (1990) tested this theory and found that cash transactions outperform stock transactions in terms of bidder abnormal return and was increasing in the portion of total payment consisting of cash. This conclusion was supported by Martynova & Renneboog (2006), Servaes (1991) and Alexandridis, Petmezas, & Travlos (2010). Based on those results I formulated hypothesis 2.1 and 2.3 as:

Hypothesis 2.1: Cash transactions result higher bidder abnormal returns than stock transactions

Hypothesis 2.3: Cash transactions result in higher bidder abnormal return than mixed transactions.

I calculate the mean difference for cash, stock and mixed method of payments. Using cash payment as the benchmark for mean abnormal return, I hypothesize the coefficients for stock and mixed payment are negative and statistical significant, which implies the market reacts positively to cash payments. For control variables, I use a variety of variables. To consider the difference in size of the bidders I include the natural logarithm of bidder market capitalization in millions of euros. Interpreting this coefficient is easy, as changing the variable by 1% will have an impact on the dependent variable equal to the coefficient divided by 100. To consider the different risk profiles of the bidders I include their betas (Drymbetas & Kyriazopoulos, 2014). Other previous researchers have also included the debt to equity (D/E) ratio as a risk measure. However, beta and the debt to equity ratio is often highly correlated. This comes from the formula for levered beta: $\beta_L = \beta_U * \left(1 + (1 - T) * \frac{D}{E}\right)$, where β_U is the unlevered beta and T equals the tax rate. Due to this correlation, I choose to only include bidder beta as risk measure. The betas are calculated using the market model. Further I include dummy variables for industry classifications. This is done to consider the differences in abnormal returns from industry to industry. Further it also helps to conclude on the direction of causation for abnormal returns. The industry dummy variables are based on the two first digits of the four digit SIC code.

Results

Table 12 below presents the results of regression number one to four using the market model CARs as the dependent variables and the benchmark is mixed payment. The model equation is as following:

$$CAR_{Bidders}[-t,+t] = \beta_0 + \beta_1 X_{Stock} + \beta_2 X_{Mixed} + \sum \beta_i C_i + \varepsilon_i$$

Where the latter is the control variables. I use dummy variables for cash and stock payments, where cash payment (stock payment) equal 1, if the payment was made in cash (stocks), and zero if not. I used a BP test, to test for heteroscedasticity, this test rejected heteroscedasticity in -1,+1 and -10,+10. But not the two middle event windows, therefore I plotted the residuals. It looks like the variance is higher for these two models, due to a couple of outliers, but it does not look like the variances are changing, thus no sign of heteroscedasticity, consequently I use normal standard errors in my regressions. The plotted residuals can be found in appendix 8.

Looking at table 12 below I find negative coefficients for stock payment, indicating a negative impact on mean abnormal return. The coefficient is significant in three of the four event window. In -10,+10 the intercept (Cash payment) is -13.6% and significant, the stock payment is -7.1% thus, equal to -20.7% mean abnormal return from stock payments. The large negative mean abnormal return is counter acted by the industry coefficients. The coefficient for mixed payment is negative for -1,+1, -5,+5 and -10,+10 and small positive for -2,+2. Common for all four coefficients are that they are insignificant and thus statistically not different from cash payment. Meaning cash payments does not result in statistically higher value creation than mixed payments.

	MM-CAR [-1,+1]		MM-CAR [-2,+2]		MM-CAR [-5,+5]		MM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.020	-0.624	-0.057	-1.601	-0.078	-1.843*	-0.136	-1.02*
Stock payment	-0.021	-1.690*	-0.012	-0.910	-0.038	-2.380**	-0.071	-2.609***
Mixed payment	-0.009	-0.893	0.001	0.082	-0.003	-0.196	-0.002	-0.097
Bidder MarketCap	0.001	0.340	0.002	0.980	0.002	0.881	0.006	1.338
Bidder beta	-0.002	-0.235	-0.004	-0.418	-0.009	-0.799	-0.003	-0.146
Manufacturing	0.028	1.642	0.035	1.829*	0.061	2.693***	0.045	1.182
Tran., Comm. & Util.	0.008	0.372	0.020	0.898	0.044	1.625	0.037	0.082
Retail and wholesale	0.022	0.951	0.035	1.331	0.079	2.573**	0.091	1.753*
Finance	0.020	1.188	0.034	1.771*	0.061	2.723***	0.070	1.843*
Services	0.001	0.062	0.006	0.289	0.030	1.252	0.026	0.628
Adjusted R^2	0.008		0.009		0.066		0.042	
Number of observations	186		186		186		186	

****,**,* indicate signifiance level of 1%, 5%, 10%*

Source: own calculations

Table 12: OLS multiple regression results for hypothesis 2.1and 2.3

Figure 8 below presents the daily AAR per method of payment as well as the accumulating effect. The graph on the right shows the accumulation of CAAR throughout the event period. It is easy to see that stock payments yield the lowest CAR for bidders, while cash payment yields the highest. This graph also shows, why it is only the stock payment coefficient, that is statistically different from cash payment and not mixed, because cash and mixed payments are too close to each other, for there to be a measurable difference. The graph to the left shows the actual daily AAR. It seems like the daily stock AAR is the most volatile, especially at day +1 where the AAR is approximately -1.5%. The results above is in line with findings by previous researchers.

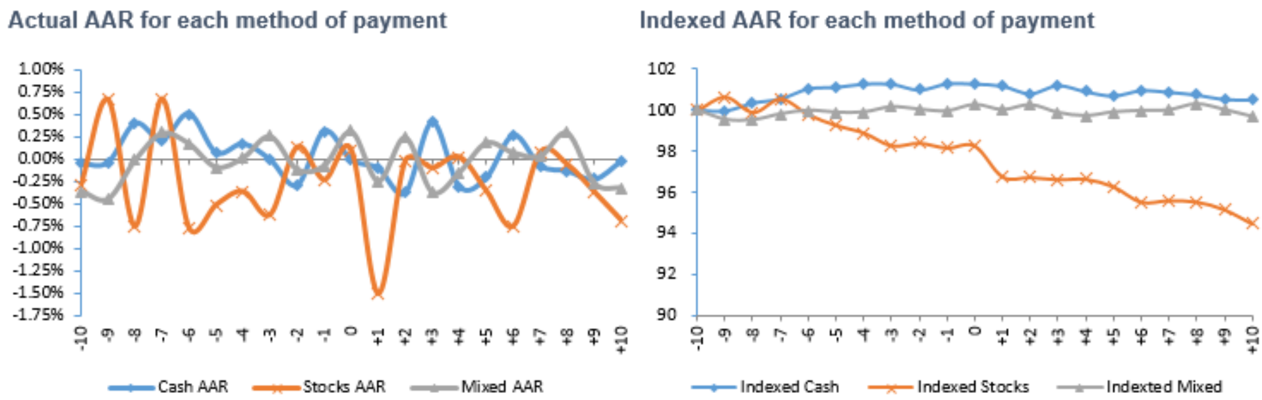


Figure 8: Daily AAR per method of payment and indexed daily AAR for accumulating effect

Appendix 4A present the results from regression five to eight using CMRM CARs as dependent variables. Here I find the stock coefficient to be negative for all event windows as well, but only significant in the two longest event windows. The -10,+10 mean abnormal return is here equal to -10.9% -6.5% = -17.4%, meaning 3.3% higher than the market model results. The mixed payment coefficients have the same sign as above in table 12 and they are still insignificant. Although the coefficients for intercept, stock and mixed payment differ a bit, the results overall confirm those presented in table 12, thus, deeming them robust.

Conclusion

Based on the regression results presented above I accept hypothesis 2.1 and conclude that bidder shareholders earn higher abnormal returns when the target is paid using cash instead of stocks. The result is in line with the signaling theory presented in the literature review, further multiple previous researchers find similar results, this include: Travlos (1987), Eckbo, Giammarino, & Heinkel (1990) and Franks, Harris, & Mayer (1988). Travlos found negative abnormal returns for stock paying bidders, while cash paying bidders earned zero abnormal returns. While Eckbo, Giammarino, & Heinkel (1990) found, abnormal returns increase in the fraction of total payment consisting of cash. For hypothesis 2.3, I must reject it, as no evidence in my sample support higher value creation from cash payment compared to mixed payment. This result is not in line with Eckbo, Giammarino, & Heinkel (1990). Since I have no information about the split between stock and cash in each mixed payment i cannot say that the result is due to high level of cash. But the regression result does suggest it, as the difference between cash and stocks is clear.

6.2.2 Hypothesis 2.2 and 2.4

The literature review and the theory section pointed out how the signaling theory also applies for targets. Turning the signaling theory upside down, means bidder management would never offer stock payment if they saw the stock as undervalued. As this would results in negative results to their shareholders. Further I mention Eckbo, Giammarino, & Heinkel (1990)'s finding of CAR increasing in portion of total payment consisting of cash. Based on that I formulated hypothesis 2.2 and 2.4 as:

Hypothesis 2.2: Cash transactions result in higher target abnormal returns than stock transactions

Hypothesis 2.4 Cash transactions result in higher target abnormal return than mixed transaction

I calculate the mean difference for cash, stock and mixed method of payments, and again use cash payment as benchmark. Therefore, I hypothesize negative and significant coefficients for both stock and mixed payment, which implies the market reacts positively to cash payment. I use dummy variables for each payment method, so cash payment (stock payment) equal 1 if the transaction is paid by cash (stocks) and zero otherwise. Further I also use dummy variables for the industry classifications. Information on pre-deal market capitalization was not available for many of the targets, consequently this control variable is excluded, as the model would seriously suffer for lack of observations. My control variables are therefore limited to betas and industry classifications.

Results

Table 13 below presents the results from regression one to four, using market model CAR as dependent variables. My regression is modelled the following way:

$$CAR_{Targets}[-t,+t] = \beta_0 + \beta_1 X_{Stock} + \beta_2 X_{Mixed} + \sum \beta_i C_i + \varepsilon_i$$

The BP test resulted in p-value between 0.29 and 0.81, thus rejecting the alternative hypothesis of heteroscedasticity for all four event windows. Consequently, no need to plot the residuals or use HAC standard errors in my regressions.

	MM-CAR [-1,+1]		MM-CAR [-2,+2]		MM-CAR [-5,+5]		MM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	0.103	1.741*	0.117	1.834*	0.116	1.604	0.111	1.484
Stock payment	-0.085	-2.210**	-0.078	-1.892*	-0.102	-2.181**	-0.102	-2.084**
Mixed payment	0.025	0.770	0.027	0.774	-0.007	-0.175	-0.017	-0.404
Target beta	-0.011	-0.315	-0.029	-0.795	-0.040	-0.985	-0.035	-0.821
Manufacturing	0.084	1.427	0.087	1.371	0.116	1.615	0.141	1.895*
Tran., Comm. & Util.	0.043	0.592	0.037	0.465	0.059	0.657	0.073	0.789
Retail and wholesale	-0.058	-0.851	-0.026	-0.356	0.058	0.696	0.047	0.537
Finance	-0.013	-0.225	-0.010	-0.162	0.007	0.099	0.026	0.350
Services	0.040	0.683	0.044	0.696	0.057	0.805	0.075	1.004
Adjusted R^2	0.080		0.052		0.041		0.039	
Number of observations	142		142		142		142	

****,**,* indicate signifiance level of 1%, 5%, 10%*

Source: own calculations

Table 13: OLS multiple regression results for hypothesis 2.2 and 2.4

Looking at table 13 I find, as expected, the stock payment coefficient to be negative and statistical significant for all four event windows. Further the coefficient is stable between -7.8% and -10.2%. Meaning targets receiving payment in bidder stocks, earn mean abnormal return that are on average 7.8% to 10.2% lower than those receiving cash. The mixed payment coefficient is positive in the two shortest event windows at around 2.5-2.7% and negative in the two longest around -0.7-1.7%. However, none of the four coefficients are significant. Thus, the abnormal return from mixed payment in indistinguishable from those of cash payments. The intercept, being the benchmark return is large and positive for all four event windows, although a bit surprising only significant in the two shortest. The coefficient for beta is negative in all four event windows, suggesting that higher beta targets have lower mean abnormal returns. This could indicate the reason for the difference between market model CAAR and CMRM CAAR discussed in section 6.1 is due to low betas, because increasing beta results in lower CAR due to increasing expected normal return. However, the beta coefficients are not significant, which makes it difficult to conclude on.

Figure 9 visualizes the daily AAR by method of payment and shows the market reactions. The Left graph shows the same results as obtained in section 6.1, that value is created on the announcement day. Here I find cash payments produce more shareholder value than stocks payments, although the results also suggest mixed payments produce the highest single announcement day returns. The accumulating effect from daily AAR is presented in the graph to the right. It shows cash payments result in more value creation than both mixed and stock payments. However, the difference between cash and mixed payment is small. This is in line with the regression results in table 13 and the signaling theory presented in the literature review. However, the extended event window of 21 days increases the possibility of noise entering the data, which affects the results. Thus, more emphasize should be put on the regression results above and less on the graphics below.

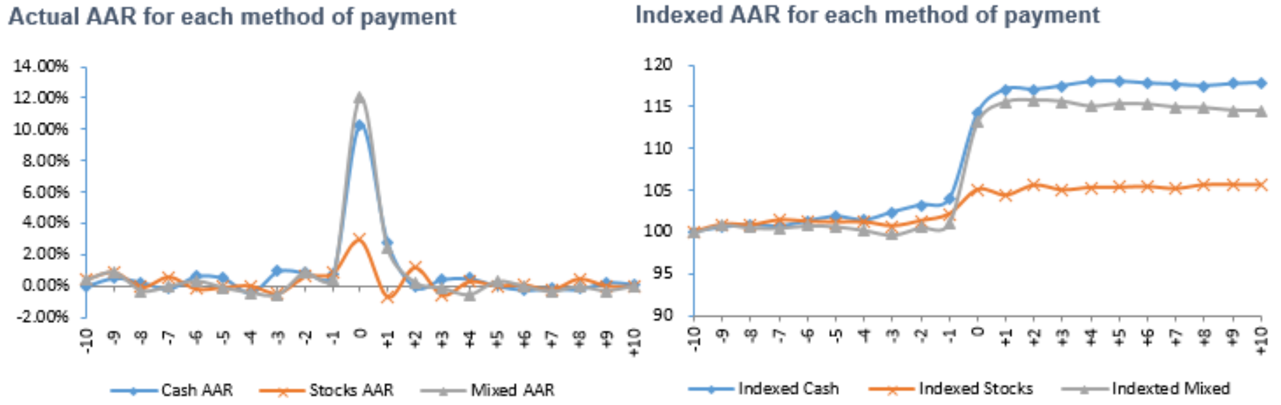


Figure 9: Daily AAR per method of payment and indexed daily AAR for accumulating effect

Appendix 4B present the results from regression five to eight. I find the same negative and significant stock payment coefficient as in table 13. However, using CMRM CARs the coefficient is only significant in the two shortest event windows. The mixed payment coefficient is positive for all four event windows, thus suggesting higher value creation than from pure cash payment. However, these coefficients are not significant either. Consequently, I can conclude these results support those from table 13, deeming them robust.

Conclusion

The results from the regression analysis suggest lower value creation from stock payment to target shareholders compared to cash payment, this by a factor of 7-10%. This result lead me to accept hypothesis 2.3. Further the regression results are supported by the daily AARs graphed in figure 9. Which clearly shows cash payment to outperform stock payment. My results for hypothesis 2.2 are in line with the signaling theory and the finding of Eckbo, Giammarino, & Heinkel (1990), Martynova & Renneboog (2006) and Alexandridis, Petmezas, & Travlos (2010). This result also implies target managers can increase shareholder value by insisting on payment in cash compared to bidder stocks. For hypothesis 2.4 I must reject it, as there is too little evidence in the data sample to support it. All eight regressions result in insignificant coefficients where six of eight are positive, indicating higher value creation from mixed payment, while only two coefficients indicate lower value creation from mixed payment. This result contradicts the one from Eckbo, Giammarino, & Heinkel (1990). As I mentioned in the conclusion for hypothesis 2.1, I don't have any information regarding the split between stocks and cash of the payments in my sample, but the results from hypothesis 2.2 suggest higher levels of cash, since the mixed coefficients are statistically indistinguishable from the cash coefficients.

6.3 Focused vs. Diversifying M&A

When companies expand their business through M&A, management often face the question of acquiring a target within the same industry, or diversify and acquire a target operating in another industry. The key to make the right decision is synergy effects from the acquisition. Conglomerates can increase market power, through cross-subsidizing, centralized purchases from suppliers and shared production facilities. While focused companies are often highly skilled, cost-cutting and innovative. The next part will test which strategy produce the most value for shareholders.

6.3.1 Hypothesis 3.1

The literature review presented previous findings that mostly supported focused acquisition as more value creating for bidder compared to diversifying. Among the researchers were Walker (2000), Healy, Palepu, & Ruback (1992) and Moeller & Schlingemann (2005). Thus, I formulated hypothesis 3.1 as:

Hypothesis 3.1: Focused acquisitions result in higher bidder abnormal returns than diversifying acquisitions

To test hypothesis 3.1, I regress the CAR as dependent variable with a dummy variable that is equal to one, if the acquisition is diversifying, and zero if focused, thereby using focused acquisitions as benchmark. I say a transaction is focused, if target and bidder share the two first digits in their four digit SIC code. I expect to find a negative and significant coefficient for diversifying deals. In my regression model, I include control variables for risk, size and industry classifications.

Results

Table 14 below presents the results from regression one to four, using market model CARs as the dependent variables. My regressions are modelled as:

$$CAR_{Bidders}[-t,+t] = \beta_0 + \beta_1 X_{Diversifying} + \sum \beta_i C_i + \varepsilon_i$$

The BP test was not able to reject heteroscedasticity for -5,+5 and -2,+2, thus I plotted the residuals.

It seems like the variance of the residuals is impacted by a few outliers, thus the BP test could not accept the null hypothesis, but the variance does not look like it is changing, i.e. do not look heteroscedastic. Thus, I use normal standard errors in the regressions. Appendix 9 shows the plotted residuals for -5,+5 and -2,+2.

	MM-CAR [-1,+1]		MM-CAR [-2,+2]		MM-CAR [-5,+5]		MM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.034	-1.060	-0.065	-1.844*	-0.098	-2.323**	-0.172	-2.4031**
Diversifying strategy	0.003	0.326	0.004	0.411	0.003	0.229	0.004	0.205
Bidder MarketCap	0.001	0.459	0.003	1.125	0.003	1.156	0.008	1.643
Bidder beta	-0.002	-0.191	-0.004	-0.466	-0.009	-0.795	-0.031	-0.157
Manufacturing	0.031	1.802*	0.035	1.858*	0.064	2.795***	0.050	1.292
Tran., Comm. & Util.	0.012	0.618	0.022	0.972	0.482	1.790*	0.045	0.982
Retail and wholesale	0.022	0.926	0.033	1.269	0.078	2.484**	0.089	1.668*
Finance	0.021	1.241	0.032	1.679*	0.059	2.599**	0.065	1.686*
Services	0.000	-0.012	0.003	0.149	0.026	1.039	0.017	0.399
Adjusted R^2	-0.002		0.010		0.039		0.007	
Number of observations	186		186		186		186	

****,**,* indicate signifiance level of 1%, 5%, 10%*
Source: own calculations

Table 14: OLS multiple regression result for hypothesis 3.1

Looking at table 14, I find the coefficient for diversifying strategy is positive, but very small and insignificant for all four event windows. This is the opposite of, what I expected based on previous findings. The results imply bidders cannot earn higher abnormal returns from focused investments. Bidders should take advantage of this finding, because the main argument against diversification was lower synergies from incomparable businesses. However, the result above shows that bidder shareholders earn the same mean abnormal return and diversifying investments is great in financial volatile times.

Even though the plotted residuals for -5,+5 and -2,+2 didn't show signs of heteroscedasticity I ran the regressions with HAC standard errors, and no materials changes to the results was found. By material changes I refer to the diversifying strategy coefficients changes from being significant to insignificant.

I plot the daily AAR for both strategies in figure 10 to see how they compare to each other. I observe the accumulating effect presented in the right-side graph suggest higher CAR from focused acquisitions, but most of the effect is created after day +4. Extending the event window increases the possibility of including noise. Therefore, more emphasize should be put on the regression results in table 14 than on the graphics below.

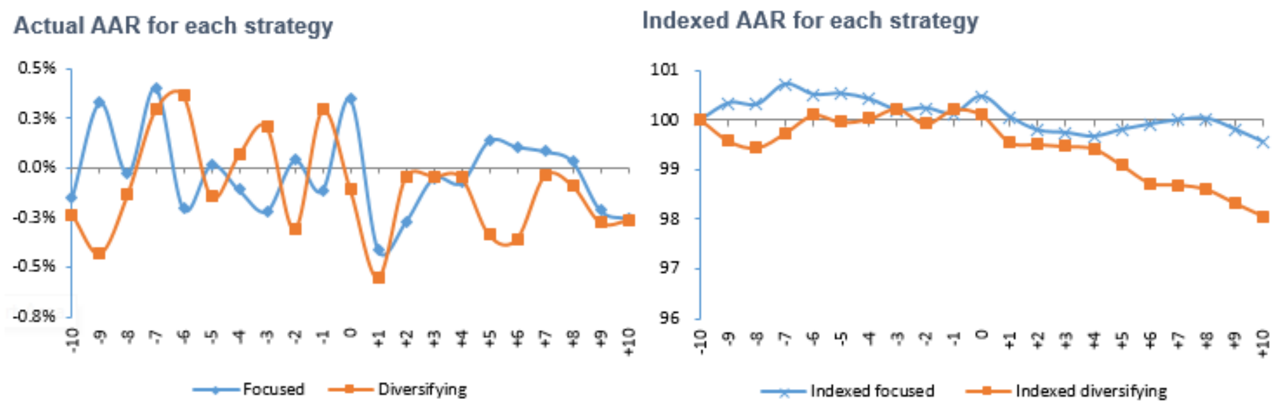


Figure 10: Daily AAR per strategy and indexed daily AAR for accumulating effect

Appendix 5A presents the results from regression five to eight. I find the diversifying coefficient to be higher than the benchmark, but still small at approximately 1% and insignificant. Thus, yielding the same results as the one presented in table 14 above. Consequently, the result seems robust.

Conclusion

Based on the regression results I reject hypothesis 3.1, and I accept zero statistical significant difference in bidder abnormal return from focused and diversifying acquisition. The results are robust to changes in event window length and method of calculation. Further I note my results contradict those presented in the literature review. The result instead supports the high market efficiency and integration mentioned in hypothesis 2.1 to 2.4, which I will discuss the implication of later in section seven.

6.3.2 Hypothesis 3.2

In hypothesis 3.2 I study the impact on target CAR from being acquired by a company using a diversifying strategy. Based on the findings and argumentation from Martynova & Renneboog (2006), that bidders are more aggressive in their bidding when the aim is to diversify the business. Thus, hypothesis 2.4 was formulated as:

Hypothesis 3.2: Diversifying acquisitions result in higher target abnormal returns than focused acquisitions

I use the same set up as in the hypothesis 3.1 with a dummy variable for diversifying strategy by bidder. The benchmark is again a non-diversifying bidder strategy. I hypothesize the coefficient for diversifying is positive and statistical significant. Further I include control variables for risk measuring and industry classifications.

Results

Table 15 presents the results from regression one to four, using market model CARs as dependent variable. The regressions are modelled as:

$$CAR_{Targets}[-t,+t] = \beta_0 + \beta_1 X_{Diversifying} + \sum \beta_i C_i + \varepsilon_i$$

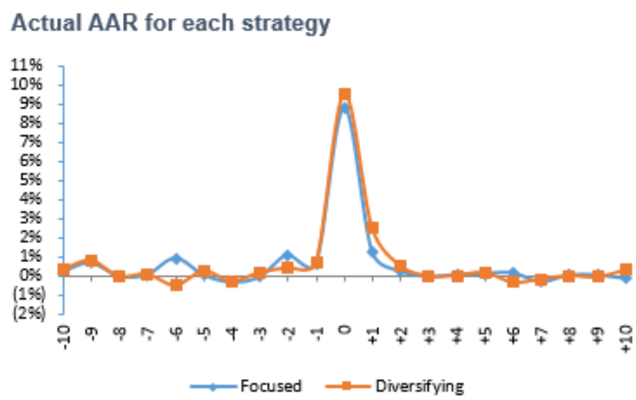
The BP test resulted in p-values between 0.19 and 0.49, thus I am rejecting heteroscedasticity for all four models. Consequently, I use normal standard errors when running my regressions.

	MM-CAR [-1,+1]		MM-CAR [-2,+2]		MM-CAR [-5,+5]		MM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	0.092	1.545	0.105	1.653	0.083	1.163	0.068	0.907
Diversifying strategy	-0.008	-0.274	-0.003	-0.088	-0.007	-0.176	0.005	0.131
Target beta	-0.014	-0.416	-0.033	-0.887	-0.005	-1.105	-0.042	-0.983
Manufacturing	0.100	1.668*	0.102	1.594	0.135	1.864*	0.161	2.150**
Tran., Comm. & Util.	0.061	0.810	0.054	0.672	0.084	0.929	0.103	1.102
Retail and wholesale	-0.042	-0.597	-0.010	-0.138	0.080	0.943	0.070	0.799
Finance	-0.014	-0.234	-0.012	-0.183	0.012	0.165	0.033	0.428
Services	0.046	0.769	0.050	0.785	0.072	0.999	0.095	1.259
Adjusted R^2	0.031		0.014		0.010		0.013	
Number of observations	142		142		142		142	

****,**,* indicate signifiance level of 1%, 5%, 10%*
Source: own calculations

Table 15: OLS multiple regression results for hypothesis 3.2

Looking at table 15 I find the diversifying coefficient is very small and negative for three shortest event windows, but positive of 0.5% in the longest. Although the coefficients have the expected negative sign, they are not significant, and thus they are indistinguishable from zero. Consequently, the results are not I line with my hypothesis, and it seems like bidder strategy does not impact the abnormal return to target shareholders.



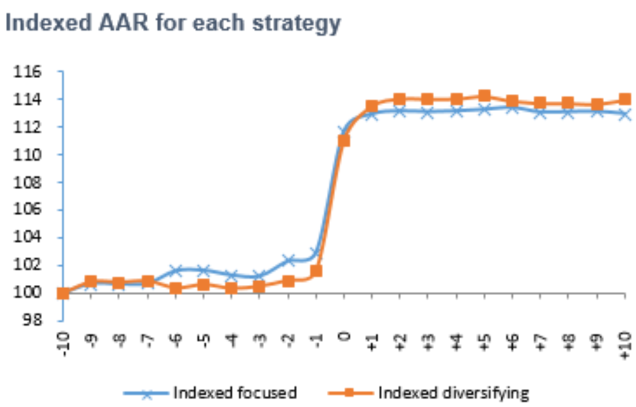


Figure 11: Daily AAR per strategy and indexed daily AAR for accumulating effect

Figure 11 above presents and visualizes the daily AAR from each strategy and the accumulating effect. I note from the left-side graph, that both strategies result in high announcement day abnormal returns, while the right-side graph indicates a very small extra premium from diversifying acquisitions. However, as seen from the regression results this effect is too small to be significant.

Appendix 5B presents the results from regression five to eight, using the CMRM CARs as dependent variables. These regressions yield the same insignificant results. Thereby I am concluding the results of equal value creation from both strategies from table 15 are robust to event window length and method of calculation.

Conclusion

Based on the regression results as well as the AAR analysis I reject hypothesis 3.2, and I accept zero difference in value creation from focused and diversifying bidder strategies. The implications are, that targets managers are unable to increase shareholder value creation by selecting a diversifying acquirer, and the result match the one obtained in hypothesis 3.1 regarding bidders. Thus, it also supports the notion of higher market efficiency and integration in Western Europe, which will be discussed in section 7 below.

6.4 Domestic vs. Cross-border M&A

This section of my research investigates the domestic and cross-border deals to see, if there are any differences in CAR for bidder and targets. The literature review listed several advantages from cross-border acquisitions, such as new markets, larger potential revenues, new supplier markets, diversification etc. (Sudarsanam, 2003). Although it also mentioned disadvantages, such as new legal systems, political systems and differences in culture (Ibid).

6.4.1 Hypothesis 4.1

When companies find themselves in a stagnant home market, and they are looking for growth opportunities or are looking to add new competencies, acquiring a foreign company can be a strategy, that at the same time is diversifying. However, acquiring a foreign company have implications. Many previous researchers have studied these implications, among them are Goergen & Renneboog (2004), Hazelkorn, Zenner, & Shivdasani (2004) and Martynova & Renneboog (2006). Their results were mixed, Hazelkorn el at. (2004) found higher CAR from cross-border deals, while Martynova &

Renneboog (2006) and Goergen & Renneboog (2004), and other, both found higher CAR from domestic deals. Based on those findings I formulated hypothesis 4.1 as:

Hypothesis 4.1: Domestic acquisitions result in higher bidder abnormal returns than cross-border acquisitions

I test the hypothesis using a dummy variable for cross-border, thereby I am using domestic deals as benchmark. I expect the cross-border coefficient to be negative with statistical significance, thus it will result in lower mean abnormal returns to bidders.

Results

Table 16 presents the results from regression one to four, using market model CARs as dependent variables. My regressions are modelled the following way:

$$CAR_{Bidders}[-t,+t] = \beta_0 + \beta_1 X_{Cross-border} + \sum \beta_i C_i + \varepsilon_i$$

The BP test accepted the alternative hypothesis of heteroscedasticity in -5,+5 and -2,+2. Consequently, I have plotted the residuals, where it looks like the variance is affected by some outliers, but it does not look to be changing over the observations. Thus, I conclude heteroscedasticity is not present in the models. Appendix 10 shows the plotted residuals for -5,+5 and -2,+2.

	MM-CAR [-1,+1]		MM-CAR [-2,+2]		MM-CAR [-5,+5]		MM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.035	-1.107	-0.067	-1.903*	-0.094	-2.209**	-0.167	-2.333**
Cross-border	-0.006	-0.582	-0.008	-0.737	0.006	0.447	0.004	0.194
Bidder MarketCap	0.001	0.579	0.003	1.262	0.003	1.007	0.007	1.542
Bidder beta	-0.001	-0.128	-0.004	-0.387	-0.009	-0.800	-0.003	-0.149
Manufacturing	0.033	1.889	0.038	1.974**	0.062	2.706***	0.049	1.257
Tran., Comm. & Util.	0.012	0.614	0.022	0.969	0.047	1.766*	0.044	0.965
Retail and wholesale	0.023	0.965	0.034	1.320	0.079	2.523**	0.090	1.698*
Finance	0.022	1.286	0.032	1.737*	0.059	2.642***	0.065	1.720*
Services	0.002	0.109	0.006	0.302	0.025	1.018	0.017	0.405
Adjusted R^2	-0.001		0.012		0.040		0.007	
Number of observations	186		186		186		186	

****,**,* indicate signifiance level of 1%, 5%, 10%*

Source: own calculations

Table 16: OLS multiple regression results for hypothesis 4.1

Looking at table 16, I find the benchmark mean return is negative for all four event windows. The mean abnormal return is significant for the three longest event windows, but not for -1,+1. Looking at the cross-border coefficient I find it, as expected, to be negative but only for the two shortest event windows, and unexpected it changes sign and becomes positive in the two longest. However, all four coefficients are less than +-1% and insignificant. Thereby indicating value creation from cross-border transaction is not different from that of domestic transactions.

Figure 12 plots the daily AAR for domestic and cross-border deals. From the right-side graph, I find cross-border deals to result in higher mean abnormal return than domestic deals. However, this difference is not statistically significant according to table 16.

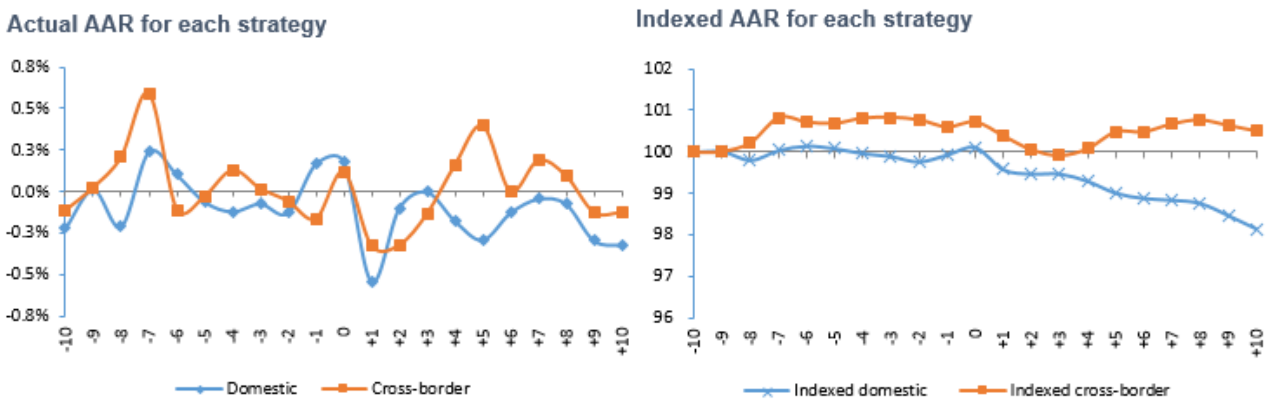


Figure 12: Daily AAR per transaction type and indexed daily AAR for accumulating effect

Appendix 6A presents the results from regression five to eight, using CMRM CARs as dependent variables. These results support the ones from table 16, because it results in the same small and insignificant cross-border coefficients, which again changes from negative to positive.

Conclusion

Based on the regression results presented above I reject hypothesis 4.1 of higher bidder abnormal returns from domestic transactions compared to cross-border. Indicating the disadvantages of entering foreign countries, such as politics, culture and new legal systems are insignificant in Western Europe, and the capital markets are very well integrated and efficient. This finding is in line with those from Lowinski, Schiereck, & Thomas (2004), who found no differences when sampling Swiss companies. They stated the European capital markets were too integrated for imperfections to arise. Further the results align with Königs & Schiereck (2008), who studied M&A involving European luxury companies, and they found no differences in abnormal returns from domestic and cross-border transactions.

6.4.2 Hypothesis 4.2

To investigate if the above results from hypothesis 4.1 also applies for target I test the same hypothesis for the targets in my sample, which is formulated based on previous results by Goergen & Renneboog (2004), Martynova & Renneboog (2006) and Moeller & Schlingemann (2005). They conclude post-acquisition integration is more difficult from cross-border acquisitions. Problems in this phase can have significantly lasting effects on future value creation from synergies (Habeck, Kröger, & Träm, 2000). Thus, I formulated hypothesis 4.2 as:

Hypothesis 4.2: Domestic acquisitions result in higher target abnormal returns than cross-border acquisitions

I use the same method mentioned in hypothesis 4.1 with a dummy variable for cross-border deals. I hypothesize a negative and significant coefficient for cross-border mean abnormal return.

Results

Table 17 below presents the results from regression one to four, using market model CARs as dependent variables. The regressions are modelled the following way:

$$CAR_{Targets}[-t,+t] = \beta_0 + \beta_1 X_{Cross-border} + \sum \beta_i C_i + \varepsilon_i$$

The BP test resulted in p-value between 0.23 and 0.46, thus I accept the null hypothesis of homoscedasticity in all models. Consequently, I use normal standard errors when running my regressions.

	MM-CAR [-1,+1]		MM-CAR [-2,+2]		MM-CAR [-5,+5]		MM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	0.087	1.554	0.104	1.733*	0.080	1.184	0.071	1.015
Cross-border	-0.018	-0.567	-0.016	-0.483	-0.023	-0.608	-0.013	-0.325
Target beta	-0.014	-0.400	-0.032	-0.858	-0.045	-1.078	-0.040	-0.941
Manufacturing	0.107	1.759*	0.108	1.662	0.143	1.955*	0.165	2.171**
Tran., Comm. & Util.	0.070	0.936	0.061	0.760	0.095	1.048	0.106	1.133
Retail and wholesale	-0.036	-0.508	-0.056	-0.074	0.087	1.024	0.073	0.825
Finance	-0.011	-0.186	-0.009	-0.141	0.016	0.217	0.035	0.457
Services	0.055	0.913	0.057	0.884	0.082	1.135	0.098	1.293
Adjusted R^2	0.033		0.015		0.012		0.014	
Number of observations	142		142		142		142	

****,**,* indicate signifiance level of 1%, 5%, 10%*
Source: own calculations

Table 17: OLS multiple regression results for hypothesis 4.2

Table 17 shows as expected a negative coefficient for cross-border transaction, indicating domestic transactions results in 1.3% to 2.3% higher CAR for targets. However, the coefficients are not significant, and thus the difference is indistinguishable from zero. Consequently, the results obtained for bidders in hypothesis 4.1 seem to extent to targets as well.

Appendix 6B presents the results from regression five to eight. The cross-border coefficient is still negative between -1.8% and -4.4%, but it is still insignificant for all four event windows.

Figure 13 plot the daily AAR for domestic and cross-border transactions. The right-side graph shows the same close relationship as indicated by the regressions results. It also indicates a higher announcement day return of 1.5-2%, compared to cross-border and in line with -1,+1 in table 17.

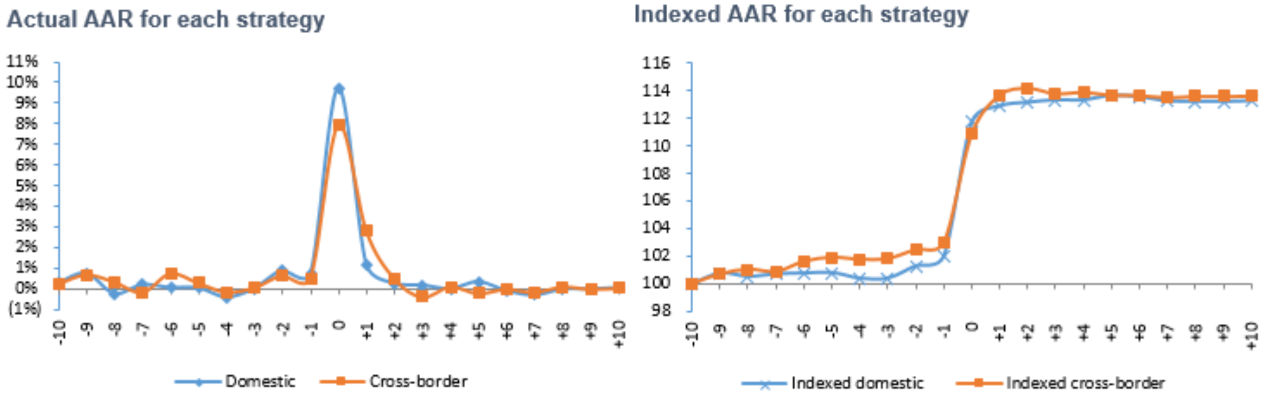


Figure 13: Daily AAR per transaction type and indexed daily AAR for accumulating effect

Conclusion

The regression results show no significant difference in the value creation from cross-border transaction compared to domestic transaction. Consequently, I reject hypothesis 4.2, although I do carefully note the coefficients indicate a small premium for domestic targets. However, I am not able to prove this premium is significant. This finding along with the one for bidders in hypothesis 4.1 is supported by Lowinski, Schiereck, & Thomas (2004), who found similar results for a Swiss sample. Also, Harris & Ravenscraft (1991) found zero difference. They both argue the higher the level of integration of the capital and factors market would be, the lower the differences between domestic and cross-border acquisitions should be.

6.5 Cash flows

This part of the thesis tests the impact of cash flows prior to announcement of transaction. I test the effect for both bidders and target. Jensen & Meckling (1976) presented a theory in which agency costs arise, when managers are reluctant to pay out excess cash. Later Jensen M. C. (1986) formulated the free cash flow hypothesis from this, and he concluded companies with high free cash flows more often make value destroying investments, although he mentioned companies with high cash flows make excellent targets for takeovers.

6.5.1 Hypothesis 5.1

Based on the free cash flow hypothesis by Jensen M. C. (1986) and the supporting findings by Owen & Yawson (2010) and Harford (1999), I formulated hypothesis 5.1 as:

Hypothesis 5.1: High bidder cash flows will have a negative effect on bidder abnormal returns.

To test this hypothesis, I regress CAR with a cash flow indicator. This indicator is equal to cash flow divided by total assets. I divide, to get the cash flow in percentage of total assets, because this indicator is more comparable across companies. Cash flow is defined as EBITDA minus interest payments, taxes, dividends, changes in net working capital and capital expenditures, I hypothesize bidders with a higher CF/TA ratio have lower CAR. Thus, I expect to find a negative and significant coefficient.

Results

Table 18 presents the results from regression one to four. The regressions are modelled as

$$CAR_{Bidders}[-t,+t] = \beta_0 + \beta_1 X_{\frac{Cash\ flow}{Total\ assets}} + \sum \beta_i C_i + \varepsilon_i$$

The BP test could not reject heteroscedasticity for the three shortest event window models. Thus, I have plotted the residuals in appendix 11. The variances seem to be impacted by outliers, which causes them to increase, but they do not seem to change over observations. Thus, no sign of heteroscedasticity is observed, and the regressions are run using normal standard errors.

	MM-CAR [-1,+1]		MM-CAR [-2,+2]		MM-CAR [-5,+5]		MM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.014	-0.456	-0.021	-0.537	-0.051	-0.960	-0.135	-1.454
Cash flow	0.007	0.528	0.016	1.182	0.044	4.043***	0.050	2.8411***
Bidder MarketCap	-0.001	-0.423	-0.001	-0.369	0.000	-0.113	0.002	0.348
Bidder beta	0.022	1.347	0.027	1.424	0.010	0.424	0.044	1.001
Manufacturing	0.024	1.526	0.024	1.390	0.047	1.820*	0.041	0.888
Tran., Comm. & Util.	0.004	0.270	0.010	0.635	0.025	0.944	0.031	0.764
Retail and wholesale	0.013	0.601	0.019	0.798	0.070	1.807*	0.098	1.895*
Finance	0.015	1.261	0.019	1.402	0.050	2.170**	0.084	2.263**
Services	0.003	0.181	0.002	0.124	0.019	0.732	0.043	1.064
Adjusted R^2	0.010		0.021		0.077		0.046	
Number of observations	147		147		147		147	

****,**,* indicate signifiance level of 1%, 5%, 10%*
Source: own calculations

Table 18: OLS multiple regression results for hypothesis 5.1

Looking at table 18 I unexpected find a positive coefficient for all four event windows. This coefficient is significant at the 1% level in the two longest event windows. For -10,+10 the coefficient of 5% is to be interpreted as an 1 % increase in cash flow / total assets equal a 5% increase in CAR. This result implies companies with higher cash flows will earn higher returns, thus it seems like the

Jensen M. C. (1986) theory does not hold, at least not for the -5,+5 and -10,+10 event windows. Although the result indicates higher cash flows are always good. One must remember the cash requirements for individual companies differ due to differences in capital structures, operating cycles, net working capital and capital expenditure. Harford (1999) studied cash holdings' impact on acquisitions, while I focus on cash flows. Although the two might be highly correlated, there is a big difference between generating cash and sitting on it. The results in table 18 suggest generating cash is value creating for bidder shareholders.

Appendix 7A presents the results from regression five to eight. These results confirm those from table 18. The cash flow coefficient is positive in all four event windows, and it is statistical significant at the 1% level for the two longest event windows, indicating positive value creation from higher cash flows. Consequently, the result seems robust to method of calculation, but sensitive to changes in event window length.

Conclusions

Based on the above regression results I can conclude higher cash flows do not lead to lower value creation. Thus, I reject hypothesis 5.1. Further, the results indicated positive value creation from higher cash flows. The result is in line with Chandera & Setia-Atmaja (2014). Who found bidder's cash flow to be marginally positively associated with shareholders' return. There are several possible explanations for this finding. First from hypothesis 2.1 to 4.2 I found strong evidence of highly integrated and very efficient capital markets in Western Europe. Such efficient markets would punish inefficient companies making poor investment choices. Thus, incentivizing companies to pay out all excess cash, that cannot be allocated to positive NPV projects.

6.5.2 Hypothesis 5.2

To finish off the research of value creation from cash flows I turn to look at the value creation from target shareholders' view. Jensen M. C. (1986) stated that companies with high cash flows are excellent targets, because these companies can support large debts and they are therefore often targeted for leveraged buy-outs by private equity funds. Further, since interest payments are tax deductible, they create tax savings, thus increasing company value. Such additional value increases bidders' willingness to pay, which again increases premiums to target shareholders Berk & DeMarzo (2014). Consequently, I formulated hypothesis 5.2 as:

Hypothesis 5.2: High target cash flows positively affect target abnormal return

To test hypothesis 5.2, I use the same approach as in hypothesis 5.1 where the cash flow coefficient is equal to cash flow in percentage of total assets. I hypothesize to find a positive and statistical significant coefficient, thus, indicating a positive relationship between CAR and cash flows.

Results

Table 19 presents the results from regression one to four, testing hypothesis 5.2 using market model CARs as dependent variables. The regressions are modelled as

$$CAR_{Targets}[-t,+t] = \beta_0 + \beta_1 X_{\frac{Cash\ flow}{Total\ assets}} + \sum \beta_i C_i + \varepsilon_i$$

The BP test resulted in p-values between 0.13 and 0.39, so I can reject the alternative hypothesis of heteroscedasticity, and assume homoscedasticity. Thus, I apply normal standard errors when running the regressions.

	MM-CAR [-1,+1]		MM-CAR [-2,+2]		MM-CAR [-5,+5]		MM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	0.007	0.097	-0.006	-0.078	-0.044	-0.519	-0.064	-0.761
Cash flow	0.063	0.267	0.091	0.382	0.083	0.312	0.248	0.921
Target beta	0.005	0.090	0.006	0.103	-0.024	-0.380	-0.014	-0.226
Manufacturing	0.188	2.419**	0.212	2.703***	0.257	2.922***	0.266	3.001***
Tran., Comm. & Util.	0.090	0.962	0.107	1.135	0.165	1.559	0.172	1.609
Retail and wholesale	-0.018	-0.159	-0.013	-0.114	0.034	0.257	0.007	0.053
Finance	0.068	0.814	0.104	1.228	0.164	1.726*	0.186	1.943*
Services	0.142	1.868*	0.168	2.183**	0.213	2.473**	0.216	2.476**
Adjusted R^2	0.035		0.052		0.051		0.063	
Number of observations	81		81		81		81	

****,**,* indicate signifiance level of 1%, 5%, 10%*
Source: own calculations

Table 19: OLS multiple regression results for hypothesis 5.2

Looking at table 19 I find a large positive coefficient for cash flow. Thus, strongly indicating high cash flows have a positive impact on target CAR. The strongest effect is observed in -10,+10 with 24.8%, while the smallest effect is seen in -1,+1 with 6.3%. However, as I feared and mentioned in the summary statistics, none of the four coefficients are statistically significant even at the 10% level, due to the standard deviation are too large. The standard deviation for -10,+10 is 26.97% and 23.6% for -1,+1. Further the model suffers from a lower number of observations, only 81, because the information on pre-deal total assets or pre-deal cash flows was unavailable. Thus, lowering the degrees of freedom, which increases the required t-statistics for each significance levels.

Appendix 7B presents the results from regression five to eight. Here I also find large and positive coefficient for cash flows, and again these are not statistically significant, the reason is still the standard deviations. Because the results from regression five to eight are not materially different from those obtained in table 19, I conclude the results are robust across the method of calculation and event windows.

Conclusion

The regression results presented above indicate a connection between high target cash flows and high target CAR. However, the standard deviations are too high to result in a t-statistic high enough for significance. Thus, I cannot accept hypothesis 5.2. These large standard deviations stem from the data sample, where some targets are very well performing, and thus attractive targets, earning high CARs, while other targets perform poorly with negative cash flows, and thus acquired cheaply leading to negative CARs. However, I do want to carefully note that high cash flows seem to be value creating for targets. The implication of this is very important, it implies target management has a strong negotiation position against bidders, if the target has a history of high and stable cash flows compared to other companies within the same industry.

7 Discussion of empirical results

The analysis section above found some expected as well as unexpected results for some the hypotheses. This section discusses potential implications and reasons for, why the results turned out this way. Table 20 below presents a summary of the empirical results.

Number	Hypothesis	Evidence
H1.1	Bidder abnormal return is zero in the event window	✓
H1.2	Target abnormal return is positive in the event window	✓
H2.1	Cash Payments result in higher bidder abnormal return than stock Payments	✓
H2.2	Cash Payments result in higher bidder abnormal return than mixed Payments	✗
H2.3	Cash Payments result in higher target abnormal return than stock Payments	✓
H2.4	Cash Payments result in higher target abnormal return than mixed Payments	✗
H3.1	Focused acquisitions result in higher bidder abnormal return than diversifying acquisitions	✗
H3.2	Diversifying acquisitions result in higher target abnormal return than focused acquisitions	✗
H4.1	Domestic acquisitions result in higher bidder abnormal return than cross-border acquisitions	✗
H4.2	Domestic acquisitions result in higher target abnormal return than cross-border acquisitions	✗
H5.1	High bidder cash flows will have negative effect on bidder abnormal returns	✗
H5.2	High target cash flows will have positive effect on target abnormal returns	(✗)

Where ✓ / ✗ implies hypothesis is accepted / rejected

Table 20: Overview of empirical results

Looking at table 20, I see the event study resulted in the expected results where bidders earned zero abnormal return upon in the event window, while targets earned large positive abnormal returns in their event windows. For bidders, the AAR was close to zero for all 21 days, with few daily AARs being significant, which made it difficult to conclude on market efficiency. Whereas for targets the day zero announcement returns were high, which suggest the clear majority of total value creation happened on the announcement day. This finding along with the indexed target AAR indicated, that Western European capital markets are very efficient, and the value impacting information is incorporated into the stock price instantly. The period prior to announcement resulted in CAAR of 2.62% (in -10,-1) to targets, with the majority of value creation happening on -2 and -1, which suggested insider trading. The same result was found by Tang & Xu (2016), who specifically studied the target stock price run-up prior to M&A announcements, and found run-ups most often are due to unreported insider trading, because they excluded other reason such as: market anticipation, toehold acquisitions and reported insider trading. Thus, it seems like insider trading is still happening despite strict regulatory overview. The period after announcement also resulted in significant abnormal returns to targets of 1.96% (in +1,+10). This abnormal return is most likely an anomaly/correction. Fama E. F. (1998) found the over-and under-reactions from investors in connection to events are common, and they occur because investors need to agree on how to price the impact from new information.

For methods of payments in hypothesis 2.1 to 2.4, I found cash payments to result in higher abnormal returns for both bidders and targets. I was not able to prove cash payments to outperform mixed payments in terms of abnormal returns for either bidders nor targets, because the coefficients were not statistically different from the cash coefficients. On the contrary, the regression results suggested higher value creation from mixed payment compared to cash payment to targets in the two shortest. However, this finding was statistically insignificant, which is impossible to give any reason and explanation for, when I don't have information on the split between stock and cash in the total payments.

Hypothesis 3.1 and 3.2 were testing whether focused or diversifying acquisition resulted in higher value creation to shareholders. I found for both bidders and targets, that there is no statistical difference between the two strategies. In hypothesis 4.1 and 4.2 I tested whether domestic or cross-border resulted in higher value creation than the other. Although I found negative cross-border coefficients for targets, they were not significant and thus, I conclude there is no difference between the value creation from the two strategies for both bidders and targets. The results from hypothesis 4.1 and 4.2 put together with those from 3.1 and 3.2 are very interesting. They indicate the Western European capital markets are very efficient and highly integrated. This comes from investors having no preferences between focused and diversification or domestic and cross-border, meaning they value the different strategies equally. The fact that investors value domestic and cross-border equally suggest the country differences, which normally causes differences in CAR, are either non-existent or very small and insignificant in Western Europe. The fact that investors value focused and diversifying transactions equally, suggest the higher anticipated synergy effects from focused transactions due to alignment of operations, are equal to the value of the lower risk which diversifying transactions brings.

Fama E. F. (1965) presented the theory of random walks in stock prices as an explanation to, why stock prices are hard to predict. In this paper, he stated an efficient market is characterized as one with a large number of profit-maximizing investors, who activity competes with each other to predict future market value of individual stocks, and where important current information is almost freely available to all participants. Therefore, in an efficient market, at any time, the listed price for a stock is a good estimate of its intrinsic value (Ibid). Relating this to my results, when markets are efficient and integrated like the Western European markets evidently are. Then countries and industry differences of bidders and targets do not matter, because bidders actively compete against each other for the most attractive targets. Thus, the highest bidder wins, (and of cause target shareholders). The highest bidder will often be the one with the highest potential synergy effects, i.e. highest willingness to pay, and when markets are integrated with few imperfection and regulatory restrictions, the winning bidder might not come from the same country or industry as the target. This is supported by Fikru & Lahiri (2014), who found the success of an acquisition does not depend on target industry and country in relation the acquirer's, but merely depends on the efficiency of the acquirer. Thus, efficient companies make good investment, while less efficient companies make less efficient investments, indicating the value creation is a result of the execution of the transaction. Whether the market efficiency extent beyond the EU markets is difficult to say, because most of the sample bidders and target originate in an EU country. Testing this, should be a consideration for future research.

When bidders are, activity competing for most attractive targets, it drives up the price, until only one bidder have not exceeded its marginal costs. Consequently, the price of the target will according to industrial organizational theory and Bertrand competition be just above, what the bidder with the second highest willingness to pay is willing to pay (Pepall, Richards, & Norman, 2014). Thus, this can also help explaining, why all value creation goes to targets' shareholders and is not split between targets' and bidders' shareholders. Further, the high level of market efficient also help validate the event study results. Because when markets are efficient, the stock price is the best estimate of the true intrinsic value of a stock, and thus the abnormal return to a stock from an M&A announcement in an efficient market is the best estimate of the true value creation from that transaction.

In the last two hypotheses, I tested the impact of cash flows on CAR for both bidders and targets. Unexpected I found a positive but significant relationship for bidders in the two longest event windows, while the coefficient is positive and insignificant in the two shortest. The two longest event windows suggested increases in CAR of 4-5 percentage point from a one percentage point increase in cash flows / total assets. This unexpected finding is supported by the findings of Fikru & Lahiri (2014) mentioned above, where efficient companies more often make good acquisitions compared to poorly performing companies. High cash flow is often a trait of well performing and efficient companies, because they are able to cut unnecessary costs and generate higher revenues.

For targets, I found an expected large positive coefficient, which suggest targets with high cash flows earn higher CARs as in accordance with Jensen M. C. (1986)'s theory. However, the standard deviations were too large due to a dispersed dataset for the cash flow coefficients to be significant. Thus, I could only conclude, that it strongly looks like high cash flows result in higher CAR, but I cannot fully conclude it. Consequently, the rejection of hypothesis 5.2 is put in brackets in table 20 above.

8 Conclusion

The purpose of this thesis was two-fold. First, I investigated if there are any abnormal returns from M&A activities to bidder and target shareholders. Secondly, I investigated which transaction characteristics that enhance or constrain the value creation. Using a data sample consisting of 189 publicly traded bidders and 142 publicly traded targets across 202 Western Europe deals, I have calculated and tested the abnormal returns for each bidder and target, where abnormal return was given by actual return minus the expected normal return. To do so, I used an event study methodology, where I first determined the event windows and estimation period. Then I used the market model to calculate the expected normal return for each stock. To test the sensitivity of the abnormal returns, I used four event window with different lengths, and for robustness checks I calculated the expected normal return using the constant-mean-return model. To test the calculated cumulative abnormal returns, I used a parametric t-test and a non-parametric rank test. The rank test was used, because the abnormal returns did not strictly follow the normal distribution, due to fat-tails. The rank test merely tested, if the average abnormal return in the event windows were higher than the abnormal return in the estimation period, and thus do not depend on the distribution of the abnormal returns.

From this analysis, I found bidders on average earn abnormal returns that are statistically indifferent from zero in all four event windows in the market model. The CMRM method resulted in negative and significant abnormal returns in the two longest event windows. The rank test agreed with the market model results from the t-test of zero abnormal returns to bidders. For targets, I found large positive and statistical significant abnormal returns of 11-14% across all event windows when using the market model. The CMRM resulted in more dispersed CAARs, but it also showed large positive abnormal returns to targets. Further the rank test supported these findings in the three longest event windows. The rank test was unable to produce a high enough t-statistics for the shortest event windows due to the standard deviation being too large. The AAR analysis indicated most value creation happens on the announcement day, with 9.1% AR, where late reactions were observed in the period after announcement, and signs of insider trading were detected in the period prior to announcement.

In the second part I used OLS multiple regression to test for potential value drivers. The value drivers were selected based on theory and previous findings by other researchers. I used a dummy variable for cash, stock and mixed payments, where the cash (stock) dummy was equal to 1 if the payment was made in cash (stock). I used cash payment as benchmark, and thus I could test both hypothesis 2.1 and 2.3 in one regression model. In the regressions, I included variable control variables, which by previous researchers were proved to have an effect. For both bidders and targets I found results consistent with the signaling theory. Thus, bidders and targets earn higher CAR, when payment is made in cash compared to stock. For mixed payment the coefficients were insignificant, thus zero statistical difference from the benchmark (cash) was found. These results were robust to method of calculation and relatively insensitive to changes in event window length, although the strongest effect was found in the longer event windows.

To test if focused or diversifying transactions lead to different CARs in hypothesis 3.1 and 3.2, I used dummy variables for each strategy. Keeping focused acquisitions as the benchmark, and using theory and previous findings to form expectation, I anticipated a negative diversifying coefficient for bidders and a positive for targets. For both bidders and targets I unexpected found no difference between focused and diversifying acquisitions. These findings, however unexpected, made more sense when considering the high level of efficiency, and how integrated Western European capital markets are. Thus, the imperfections that normally create differences do not exist in those capital markets.

In testing if domestic transactions create more value than cross-border transaction in hypothesis 4.1 and 4.2, I found similar returns to those in hypothesis 3.1 and 3.2, where zero significant differences were observed. This finding is again a sign of high level of market efficiency and integration in Western Europe, where profit-maximizing bidders compete to acquire the most attractive targets with no regards for country borders or industry classifications.

In the last part of the multiple regression analysis I investigated the impact from cash flows. For bidders, I found a positive relation between cash flows and CAR. A result that contradicted previous findings and theory. It seems like the efficiency of Western European capital markets extent to monitoring, because evidence points to cash rich firms making positive abnormal returns, which contradict the notice of cash rich firms often sit on poorly investing cash holdings instead of paying it out. For targets, I found a positive relationship between cash flows and CAR, which support Jensen's free cash flow hypothesis. However, the cash flow coefficients were not significant due to the standard deviation being too large. Thus, to confirm this hypothesis more data is needed, but was not available.

To answer the research question, I can conclude targets earn large positive abnormal returns from M&A, while bidders earn zero abnormal returns. These results showed some level of sensitivity to changes in event window length and method of calculation. In the search for value drivers, I found cash payment to be one, while payment in stock is value destroying. Further high cash flows for both bidders and targets also seems to be a value driver; however, more significant evidence is needed to make such conclusion. My findings regarding underlying strategies were not in line with previous findings, thus no value drivers were found here. Instead they presented evidence of very efficient and integrated Western European capital markets, with only a few and insignificant imperfections. However, to conclude on market efficiency more data and analyses are needed, but was not available.

9 Considerations for future research

Given the discussed strengths and limitations of this thesis, there are several points, where future researcher can begin. Firstly, there are several ways of defining and measuring value creation, but this thesis only applies one. It would be interesting to see how my results hold up against a new methodology or a different definition of, and measure for, value creation.

One of the bigger drawbacks of my thesis is the sample size. My data sample includes relatively few observations, further many variables have a significant range, which results in a large standard deviations and thus low t-statistics. By extending the data sample future researchers might be able to obtain more stable and robust results. The sample of this thesis was limited to publicly listed companies, by including unlisted companies the sample size could increase significantly, however, other measures of value creation would then have to be established.

This thesis concludes with a discussion on market efficiency and the impact from high performing bidders compared to poor performing bidders. Those would be some of the key areas I would focus more on, if I had to conduct future research on this topic. It would be interested to include a variable like a three-year average of return on equity or return on assets as a measure for bidder performance prior to an acquisition. Measuring market efficiency is more difficult, but looking at market volumes and liquidity is a good start to get a picture of market activity. Then one can compare the CARs from markets with high activity to those with less activity.

There are other aspects not included in this thesis, which have an impact on abnormal returns from M&A. Future researchers could consider aspects such as ownership structure, i.e. if any large (>5%) shareholders exist, for both bidders and targets, and further consider hostile vs. friendly takeover attempts. Because the impact from these characteristics can be significant. For example, recently when the Danish logistics giant DSV acquire Panalpina from Switzerland. Panalpina had one large shareholder, who opposite to many smaller shareholders, quickly rejected the first bids, thereby increasing the abnormal return for themselves and the rest of Panalpina's shareholders, on the expense of DSV's shareholders. I have tried to obtain information about ownerships structures, unfortunately my dataset ended up with a lot of blanks, especially for delisted targets.

10 Bibliography

Aevoae, G. M., Dicu, R., & Mardiros, D. (2018). How do the foreign direct investment flow? The case of the cross-border M&As in the European Union. *Accounting and Management Information Systems, 17*(4), 641-662.

Ahern, K. R. (2009). Sample selection and event study estimation. *Journal of Empirical Finance, 16*, 466-482.

Alexandridis, G., Antypas, N., & Travlos, N. (2017). Value creation from M&A: New evidence. *Journal of Corporate Finance, 45*, 632-650.

Alexandridis, G., Mavrovitis, C. F., & Travlos, N. G. (2011). How have M&As changed? Evidence from the sixth merger wave. *The European Journal of Finance, 18*(8), 663-688.

Alexandridis, G., Petmezas, D., & Travlos, N. (2010). Gains from Mergers and Acquisitions Around the World: New Evidence. *Financial Management*, 1671-1695.

Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research, 6*(2), 159-178.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9*, 3-18.

Bartholdy, J., Olson, D., & Peare, P. (2007). Conducting Event Studies on a small stock exchange. *The European Journal of Finance, 13*(3), 227-252.

Berk, J., & DeMarzo, P. (2014). *Corporate Finance* (Vol. 3rd). London: Pearson Educated Limited.

Bowman, R. G. (1983). Understanding and Conducting Event Studies. *Journal of Business Finance & Accounting, 10*(4), 561-584.

Bradley, M., Desai, A., & Kim, E. (1988). Synergistic gains from corporate acquisitions and their division between the stocksholders of target and acquiring firms. *Journal of Financial Economics, 21*, 3-40.

Brown, S. J., & Warner, J. B. (1985). Using Daily Stock Returns: The Case of Event Studies. *Journal of Financial Economics, 14*, 3-31.

Bruner, R. (2002). Does M&A pay? A Survay of Evidence for the Decision-Maker. *Journal of Applied Finance*, 48-68.

Campa, J. M., & Hernando, I. (2004). Shareholder Value Creation in European M&As. *European Financial Management, 10*(1), 47-81.

Campbell, C. J., & Wesley, C. E. (1993). Measuring security price preformance using daily NASDAQ returns. *Journal of Financial Economics, 33*(1), 73-92.

Campbell, J. Y., Lo, A. W., & MacKinley, A. C. (1997). *The Econometrics of Financial Markets.* Princeton, New Jersey: Princeton University Press.

Chandera, Y., & Setia-Atmaja, L. (2014). Cross-Border Mergers and Acquisitions in China: A Test of the Free Cash Flow Hypothesis. *Indonesian Capital Market Review, VI*(2), 87-97.

Chu, Y., & Liu, P. (2016). A direct test of the Free Cash Flow Hypothesis: Evidence from Real Estate Transactions. *Journal of Real Estate Finance and Economics, 52*, 543-558.

Corrado, C. J. (1989). A nonparametric test for abnormal security-price performance in event studies. *Journal of Financial Economics, 23*, 385-395.

Corrado, C., & Zivney, T. (1992). The Specification and Power of the Sign Test in Event Study Hypothesis Tests Using Daily Stock Returns. *Journal of Financial and Quantitative Analysis, 27*(3), 465-478.

Cowan, A. R., & Sergeant, A. M. (1996). Trading frequent and event study test specification. *Journal of Banking & Finance, 20*, 1731-1757.

Diepold, B., Feinberg, R., Round, D., & Tustin, J. (2008, February). Merger Impacts on Investor Expectations: An Event Study for Australia. *International Journal of the Economics of Business, 15*(1), 45-62.

Dimson, E. (1979). Risk Measurement when Shares are Subject to Infrequent Trading. *Journal of financial economics, 7*, 197-226.

Doukas, J., Holmén, M., & Travlos, N. (2001). Corporate Diversification and Performance: Evidence from Swedish Conglomerate and Non-Conglomerate Acquisitions. *Department of Finance, 53*.

Drymbetas, E., & Kyriazopoulos, G. (2014). Short-term Stock Price Behaviour around European Cross-border Bank M&As. *Journal of Applied Finance & Banking, 4*(3), 47-70.

Dyckman, T., Philbrick, D., & Stephan, J. (1984). A Comparision of Event Study Methodologies Using Daily Stock Returns: A Simulation Approach. *Journal of Accounting Research, 22*, 1-30.

Eckbo, B. E., & Thorburn, K. S. (2000). Gains to Bidder Firms Revisited: Domestic and Foreign Acquisition in Canada. *Journal of Financial and Quantitative Analysis, 35*(1), 1-25.

Eckbo, B. E., Giammarino, R. M., & Heinkel, R. L. (1990). Asymmetric Information and the Medium of Exchange in Takeovers: Theory and Tests. *The review of Financial Studies, 3*(3), 651-675.

Fama, E. F. (1965). Random Walks in Stock Market Prices. *Financial Analysts Journal*, 55-59.

Fama, E. F. (1976). *The foundations of finance.* New York: Basic books, Inc. Publishers.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics, 49*, 283-306.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance, 47*(2), 427-465.

Fama, E. F., Fisher, L., Jensen, M., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review, 10*(1), 1-21.

Fikru, M. G., & Lahiri, S. (2014). Cross-border mergers with flexible policy regime: The role of efficiency and market size. *Journal of The Japanese and International Economies, 34*, 58-70.

Franks, J. R., Harris, R. S., & Mayer, C. (1988). Means of Payment in Takeovers: Results for the United Kingdom and the United States. *Corporate Takeovers: Causes and Consequences*, 221-264.

Goergen, M., & Renneboog, L. (2004). Shareholder Wealth Effects of European Domestic and Cross-Border Takeover Bids. *CentER Discussion Paper, 50*.

Golbe, D. L., & White, L. J. (1993). Catch A Wave: The Time Series Behavior Of Mergers. *Review of Economics & Statistics, 75*(3), 493-499.

Graca, T., & Masson, R. (2016). A structural event study for M&As: an apllication in corporate governance. *Applied Economics, 48*(45), 4350-4365.

Habeck, M. M., Kröger, F., & Träm, M. R. (2000). *After the merger: seven strategies for successful post-merger integration.* London: Prentice Hall, Pearson Educated.

Halcoussis, D. (2005). *Understanding Econometrics.* Mason, Ohio: Thomson Learning / South-Western.

Harford, J. (1999). Corporate Cash Reserves and Acquisitions. *The Journal of Finance, 54*(6), 1969-1997.

Harris, R., & Ravenscraft, D. (1991). The Role of Acquisitions in Foreign Direct Investment: Evidence from the U.S. Stock Market. *The Journal of Finance, XLVI*(3), 825-844.

Hazelkorn, T., Zenner, M., & Shivdasani, A. (2004). Creating Value With Mergers and Acquisitions. *Journal of Applied Corporate Finance, 16*(2-3), 81-90.

Healy, P., Palepu, K., & Ruback, R. (1992). Does corporate performance improve after mergers? *Journal of Financial Economics, 31*, 135-175.

Houston, J., James, C., & Ryngaert, M. (2001). Where do merger gains come from? Bank mergers from the perspective of insiders and outsiders. *Journal of Financial Economics, 60*, 285-331.

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance and Takeovers. *American Economic Review, 76*(2), 323-329.

Jensen, M., & Meckling, W. (1976). Theory of the firm: Managerial behavoir, agency costs and ownership structure. *Journal of Financial Economics, 3*, 305-360.

Königs, A., & Schiereck, D. (2008). Combined in Luxury: M&A Announcement Effects and Capital Market integration in Europe. *The Icfai Journal of Mergers&Acquisitions, V*(1), 30-56.

Klinger, D., & Gurevich, G. (2014). *Event Studies for Financial Research - A Comprehensive Guide.* New York: Palgrave Macmillan US.

Kothari, S., & Warner, J. B. (2007). Econometrics in event studies. In E. B. Eckbo, *Handbook of Corporate Finance* (pp. 3-36). Hanover, New Hampshire: Elsevier.

Lang, L. H., Stulz, R. M., & Walkling, R. A. (1991). A test of the free cash flow hypothesis - The case of bidder returns. *Journal of Financial Economics, 29*, 315-335.

Li, Y. (2018). Dissecting bidder security returns on payment methods . *Journal of Banking and Finance, 96*, 207-220.

Lowinski, F., Schiereck, D., & Thomas, T. (2004). The Effect of Cross-Border Acquisitions on Shareholder Wealth - Evidence from Switzerland. *Review of Quantitative Finance and Accounting, 22*, 315-330.

MacKinley, A. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature, XXXV*, 13-39.

Martynova, M., & Renneboog, L. (2006). Mergers and Acquisition in Europe. *Discussion paper, 2006-003*.

Martynova, M., & Renneboog, L. (2008). A century of corporate takeovers: What have we learned and where do we stand? *Journal of Banking & Finance, 32*, 2148-2177.

Martynova, M., & Renneboog, L. (2011). The performance of the European Market for Corporate Control: Evidence from the Fifth Takeover Wave. *European Finanancial Managament, 17*(2), 208-259.

Mergermarket. (2018). *Deal Drivers EMEA.* London: mergermarkets.com.

Moeller, S., & Schlingemann, F. (2005). Global diversificantion and bidder gains: A comparision between cross-border and domestic acquisitions. *Journal of Banking & Finance, 29*, 533-564.

Mulherin, J., & Boone, A. (2000). Comparing acquisition and divestitures. *Jornal of Corporate Finance, 6*, 117-139.

Myers, S., & Majluf, N. (1984). Corporate Financing and Investment Decisions hen Firms have Information that Investors do not have. *Journal of Financial Economics, 13*, 187-221.

Owen, S., & Yawson, A. (2010). Human development and cross border acquisitions. *Journal of Empirical Finance, 17*, 689-701.

Pepall, L., Richards, D., & Norman, G. (2014). *Industrial Organization: Contemporary theory and empirical applications.* Hobooken, New Jersey, USA: Wiley.

Reinganum, M. R. (1981). Misspecification of Capital Asset Pricing Empirical Anomalies Based on Earnings' Yields and Market values. *Journal of Financial Economics, 9*, 19-46.

Savor, P., & Lu, Q. (2009). Do Stock Mergers create Value for Acquirers? *The Journal of Finance, LXIV*(3), 1061-1097.

Scholes, M., & Williams, J. (1977). Estimating Betas from Nonsynchronous Data. *Journal of Financial Economics, 5*, 309-327.

Servaes, H. (1991). Tobin's Q and the Gains from Takeovers. *The Journal of Finance, 46*(1), 409-419.

Seyhun, H. N. (1986). Insiders' profits, costs of trading, and market efficiency. *Journal of Financial Economics, 16*, 189-212.

Shleifer, A., & Vishny, R. (2003). Stock market driven acquisitions. *Journal of Financial Economics, 70*, 295-311.

Stock, J. H., & Watson, M. W. (2015). *Introduction to Econometrics* (3. ed., Updated global ed. ed.). New York: Pearson Education Limited.

Sudarsanam, S. (2003). *Creating Value from Mergers and Acquisitions - The Challaenges.* London: Pearson Educated Limited.

Sudarsanam, S., & Mahate, A. (2003). Glamour Acquirers, Method of Payment and Post-acquisition Performance: The UK Evidence. *Journal of Business Finance & Accounting, 30*(1), 299-341.

Tang, Z., & Xu, X. (2016). What Causes the Target Stock Price Run-Up Prior to M&A Announcements? *Journal of Accounting and Finance, 16*(6), 106-120.

The Boston Consulting Group. (2017). *The 2017 M&A Report - The Technology Takeover.* Boston: The Boston Consulting Group.

Townsend, M., Surane, J., Orr, E., & Cannon, C. (2017, November 8). *America's Retail Apocalypse' Is Really Just beginning*. (N. Turner, Editor) Retrieved April 16, 2019, from Bloomberg.com: https://www.bloomberg.com/graphics/2017-retail-debt/

Travlos, N. (1987). Corporate Takeover Bids, Method of Payment, and Bidding Firms' Stock Returns. *The Journal of Finance, 42*(4), 943-963.

Uysal, V. B. (2011). Deviation from the target capital structure and acquisition choices. *Journal of Financial Economics, 102*, 602-620.

Walker, M. (2000). Corporate Takeovers, Strategic Objectives, and Acquiring-Firm Shareholder Wealth. *Financial Management*, 53-66.

Wooldridge, J. M. (2009). *Introductory Econometrics: A modern approach.* Mason, Ohio: Cengage Learning.

11 List of appendices

- Appendix 1: List of all bidders and targets included in the data sample
- Appendix 2: List of stock indexes used as proxy for markets
- Appendix 3: Distribution of bidder AR and target AR
- Appendix 4: Regression results using CMRM CARs as dependent variables in hypothesis 2.1 to 2.4
- Appendix 5: Regression results using CMRM CARs as dependent variables in hypothesis 3.1 and 3.2
- Appendix 6: Regression results using CMRM CARs as dependent variables in hypothesis 4.1 and 4.2
- Appendix 7: Regression results using CMRM CARs as dependent variables in hypothesis 5.1 and 5.2
- Appendix 8: Plotted residuals for Hypothesis 2.1 & 2.3
- Appendix 9: Plotted residuals for Hypothesis 3.1
- Appendix 10: Plotted residuals for Hypothesis 4.1
- Appendix 11: Plotted residuals for Hypothesis 5.1

11.1 Appendix 1

List of all transactions included in final data sample
The table includes all transactions where either the bidder, target or both are included in the final dataset. The table include my deal number, year of announcement, bidder name, target name and a comment on whether the bidder, target or both are included in the final data sample.

Deal No.	Year	Bidder	Target	Comment
1	2015	ROYAL DUTCH SHELL PLC	BG GROUP PLC	Both
2	2014	MEDTRONIC HOLDINGS LTD	COVIDIEN PLC	Both
4	2018	HOCHTIEF AG	ABERTIS INFRAESTRUCTURAS SA	Both
5	2017	ESSILOR INTERNATIONAL SA	LUXOTTICA GROUP SPA	Both
6	2015	HOLCIM LTD	LAFARGE SA	Both
7	2015	NOKIA OYJ	ALCATEL-LUCENT SA	Both
9	2015	KONINKLIJKE AHOLD NV	DELHAIZE GROUP SA	Both
10	2018	MELROSE INDUSTRIES PLC	GKN PLC	Both
11	2016	MYLAN NV	MEDA AB	Both
12	2014	KLEPIERRE SA	CORIO NV	Both
13	2014	AVIVA PLC	FRIENDS LIFE GROUP LTD	Both
14	2017	SAFRAN SA	ZODIAC AEROSPACE SA	Both
15	2016	TECHNIPFMC PLC	TECHNIP SA	Both
16	2017	THALES SA	GEMALTO NV	Bidder only
17	2017	GECINA SA	EUROSIC SA	Both
18	2015	LIBERTY GLOBAL PLC	CABLE & WIRELESS COMMUNICATIONS PLC	Both
19	2018	INFORMA PLC	UBM PLC	Both
20	2014	DEUTSCHE ANNINGTON IMMOBILIEN SE	GAGFAH SA	Both
21	2017	STANDARD LIFE PLC	ABERDEEN ASSET MANAGEMENT PLC	Both
22	2017	TESCO PLC	BOOKER GROUP PLC	Both
23	2015	PADDY POWER PLC	BETFAIR GROUP PLC	Both
24	2018	SANOFI SA	ABLYNX NV	Both
25	2014	PERRIGO COMPANY PLC	OMEGA PHARMA SA/NV	Bidder only
26	2016	BANCO BPM SPA	BANCA POPOLARE DI MILANO SCARL	Bidder only
27	2017	JOHN WOOD GROUP PLC	AMEC FOSTER WHEELER PLC	Both
28	2018	VONOVIA SE	BUWOG AG	Both
29	2017	GVC HOLDINGS PLC	LADBROKES CORAL GROUP PLC	Both
30	2014	ORANGE SA	JAZZTEL PLC	Target only
32	2017	ELIS SA	BERENDSEN PLC	Both
33	2016	VONOVIA SE	CONWERT IMMOBILIEN INVEST SE	Both
34	2017	TRANSOCEAN LTD	SONGA OFFSHORE SE	Both
35	2018	TELE2 AB	COM HEM HOLDING AB	Both
36	2015	LIVANOVA PLC	SORIN SPA	Both
37	2015	BANCO DE SABADELL SA	TSB BANKING GROUP PLC	Both
38	2014	CARPHONE WAREHOUSE GROUP PLC	DIXONS RETAIL PLC	Both
39	2017	VIVENDI SA	HAVAS SA	Both

40	2018	CYBG PLC	VIRGIN MONEY HOLDINGS (UK) PLC	Both
41	2015	ARRIS INTERNATIONAL LTD	PACE PLC	Both
42	2015	DUFRY AG	WORLD DUTY FREE SPA	Both
43	2014	NEW STERIS LTD	SYNERGY HEALTH PLC	Both
44	2018	COMPAGNIE GENERALE DES ETABLISSEMENTS MICHELIN SCA	FENNER PLC	Both
45	2015	DELPHI AUTOMOTIVE PLC	HELLERMANNTYTON GROUP PLC	Both
46	2015	GVC HOLDINGS PLC	BWIN.PARTY DIGITAL ENTERTAINMENT PLC	Both
47	2016	CASTELLUM AB	FASTIGHETSAKTIEBOLAGET NORRPORTEN AB	Bidder only
48	2018	TOTAL SA	DIRECT ENERGIE SA	Both
49	2014	BOLLORE SA	HAVAS SA	Both
50	2017	YIT OYJ	LEMMINKAINEN OYJ	Both
51	2014	HELVETIA HOLDING AG	SCHWEIZERISCHE NATIONAL-VERSICHERUNGS-GESELLSCHAFT AG	Both
52	2016	KONECRANES OYJ	TEREX MHPS GMBH	Bidder only
53	2014	KORIAN SA	MEDICA SA	Bidder only
54	2014	SSAB AB	RAUTARUUKKI OYJ	Both
55	2016	FNAC SA	DARTY PLC	Both
56	2016	MUNKSJO OYJ	AHLSTROM OYJ	Both
57	2014	GREENE KING PLC	SPIRIT PUB COMPANY PLC	Both
58	2014	GEBERIT AG	SANITEC OYJ	Both
60	2016	TOTAL SA	SAFT GROUPE SA	Both
61	2015	MERLIN PROPERTIES SOCIMI SA	TESTA INMUEBLES EN RENTA SA	Bidder only
62	2017	INMOBILIARIA COLONIAL SOCIMI SA	AXIARE PATRIMONIO SOCIMI SA	Both
63	2015	JUST RETIREMENT GROUP PLC	PARTNERSHIP ASSURANCE GROUP PLC	Both
65	2015	ALSTRIA OFFICE REIT-AG	DO DEUTSCHE OFFICE AG	Bidder only
66	2018	RAMSAY GENERALE DE SANTE SA	CAPIO AB	Both
67	2018	GIVAUDAN SA	NATUREX SA	Both
68	2015	TELE COLUMBUS AG	PRIMACOM AG	Bidder only
69	2014	ALLIANZ SE	YAPI KREDI SIGORTA SA	Bidder only
70	2014	SOPRA GROUP SA	GROUPE STERIA SCA	Both
71	2016	CAIXABANK SA	BANCO BPI SA	Both
73	2014	ATOS SE	BULL SA	Both
74	2016	CAIRO COMMUNICATION SPA	RCS MEDIAGROUP SPA	Both
75	2014	OPHIR ENERGY PLC	SALAMANDER ENERGY PLC	Both
76	2017	IP GROUP PLC	TOUCHSTONE INNOVATIONS PLC	Both
77	2016	VECTURA GROUP PLC	SKYEPHARMA PLC	Both
78	2014	IMERYS SA	S&B INDUSTRIAL MINERALS SA	Bidder only
80	2015	VIVENDI SA	SOCIETE D'EDITION DE CANAL PLUS SA	Target only
81	2016	VIVENDI SA	GAMELOFT SE	Target only
82	2018	RINGKJOBING LANDBOBANK A/S	NORDJYSKE BANK A/S	Both

83	2018	GRAINGER PLC	GRIP REIT PLC	Bidder only
84	2018	ADLER REAL ESTATE AG	BRACK CAPITAL PROPERTIES NV	Both
85	2018	CARETECH HOLDINGS PLC	CAMBIAN GROUP PLC	Both
87	2014	SWISSCOM AG	PUBLIGROUPE SA	Both
88	2017	TLG IMMOBILIEN AG	WCM BETEILIGUNGS & GRUNDBESITZ AG	Both
89	2016	RPC GROUP PLC	BRITISH POLYTHENE INDUSTRIES PLC	Both
90	2017	MONDI PLC	POWERFLUTE GROUP HOLDINGS OY	Bidder only
91	2018	SANDVIK AB	METROLOGIC GROUP SAS	Bidder only
92	2015	SWECO AB	GRONTMIJ NV	Both
94	2016	INDRA SISTEMAS SA	TECNOCOM TELECOMUNICACIONES Y ENERGIA SA	Both
96	2016	DEUTSCHE POST AG	UK MAIL GROUP PLC	Both
97	2017	TELEVISION FRANCAISE 1 SA	AUFEMININ SA	Both
98	2015	MAUREL & PROM SA	MPI SA	Both
99	2014	KUKA AG	SWISSLOG HOLDING AG	Both
100	2016	ARBONIA AG	LOOSER HOLDING AG	Both
101	2015	VIOHALCO SA/NV	ELVAL HOLDINGS SA	Bidder only
102	2016	CENERGY HOLDINGS SA/NV	CORINTH PIPEWORKS HOLDINGS SA	Target only
103	2016	LEROY SEAFOOD GROUP ASA	HAVFISK ASA	Both
104	2017	ICADE SA	ANF IMMOBILIER SA	Both
105	2016	AKIS GAYRIMENKUL YATIRIM ORTAKLIGI AS	SAF GAYRIMENKUL YATIRIM ORTAKLIGI AS	Both
106	2014	TECHNICAL OLYMPIC SA	MOCHLOS SA	Both
107	2017	KINDRED GROUP PLC	32RED PLC	Both
108	2017	TAMEDIA AG	GOLDBACH GROUP AG	Both
109	2015	CIRCASSIA PHARMACEUTICALS PLC	AEROCRINE AB	Both
110	2017	CLINIGEN GROUP PLC	QUANTUM PHARMA PLC	Both
111	2015	CATENA AB	TRIBONA AB	Both
112	2016	BANCA IFIS SPA	GE CAPITAL INTERBANCA SPA	Bidder only
114	2015	CARREFOURSA CARREFOUR SABANCI TICARET MERKEZI AS	KILER ALISVERIS HIZMETLERI VE GIDA SAN TIC AS	Both
115	2018	BELL FOOD GROUP AG	HUGLI HOLDING AG	Bidder only
116	2017	KARO PHARMA AB	WEIFA ASA	Both
117	2017	PALLINGHURST RESOURCES LTD	GEMFIELDS PLC	Target only
119	2017	HAGAR HF	OLIUVERZLUN ISLANDS HF	Bidder only
120	2016	CENERGY HOLDINGS SA/NV	HELLENIC CABLES HOLDINGS SA	Target only
121	2016	TIKEHAU CAPITAL PARTNERS SAS	SOCIETE ALSACIENNE ET LORRAINE DE VALEURS D'ENTREPRISES ET DE PARTICIPATIONS SA	Target only
122	2014	BRAVOFLY RUMBO GROUP NV	LASTMINUTE.COM LTD	Bidder only
123	2017	HIGHLIGHT COMMUNICATIONS AG	CONSTANTIN MEDIEN AG	Both
125	2015	VIOHALCO SA/NV	SIDENOR HOLDINGS SA	Both

126	2014	HEADER COMPRESSION SWEDEN HOLDING AB	STENDORREN FASTIGHETER AB	Target only
127	2016	QIAGEN NV	EXIQON A/S	Both
128	2015	WILLIAM DEMANT HOLDING A/S	AUDIKA GROUPE SA	Both
130	2015	DEMIRE DEUTSCHE MITTELSTAND REAL ESTATE AG	FAIR VALUE REIT-AG	Bidder only
131	2014	IP GROUP PLC	FUSION IP PLC	Both
132	2017	NATIXIS SA	DALENYS SA	Both
133	2015	MATCHTECH GROUP PLC	NETWORKERS INTERNATIONAL PLC	Both
134	2014	AMADEUS IT HOLDING SA	I:FAO AG	Both
135	2016	UNTERNEHMENS INVEST AG	ALL FOR ONE STEEB AG	Both
136	2016	MIGROS TICARET AS	TESCO KIPA KITLE PAZARLAMA TIC GIDA SAN AS	Both
138	2014	BIOALLIANCE PHARMA SA	TOPOTARGET A/S	Both
141	2015	NCC GROUP PLC	ACCUMULI PLC	Both
142	2015	ROCKHOPPER EXPLORATION PLC	FALKLAND OIL & GAS LTD	Both
143	2014	BRAEMAR SHIPPING SERVICES PLC	ACM SHIPPING GROUP PLC	Both
144	2015	TIETO OYJ	SOFTWARE INNOVATION AS	Bidder only
147	2016	EVOTEC AG	CYPROTEX PLC	Both
148	2018	HIGHLIGHT COMMUNICATIONS AG	CONSTANTIN MEDIEN AG	Both
149	2017	ACCENTURE PLC	SINNERSCHRADER AG	Both
151	2015	MOBIMO HOLDING AG	DUAL REAL ESTATE INVESTMENT SA	Bidder only
152	2016	AXFOOD AB	MATSE HOLDING AB	Both
153	2014	ROCKHOPPER EXPLORATION PLC	MEDITERRANEAN OIL & GAS PLC	Both
154	2018	TT ELECTRONICS PLC	STADIUM GROUP PLC	Both
158	2014	ACANDO AB	CONNECTA AB	Both
159	2014	ADLER REAL ESTATE AG	ESTAVIS AG	Both
160	2015	SCANFIL OYJ	PARTNERTECH AB	Both
161	2014	AEVIS HOLDING SA	VICTORIA-JUNGFRAU COLLECTION AG	Bidder only
162	2018	PUBLICIS GROUPE SA	SOFT COMPUTING SA	Both
164	2018	ENGIE SA	ELECTRO POWER SYSTEMS SA	Both
165	2018	MEDICAL PROGNOSIS INSTITUTE A/S	ONCOLOGY VENTURE SWEDEN AB	Target only
167	2015	ALMA MEDIA OYJ	TALENTUM OYJ	Both
168	2014	PORR AG	UBM REALITATENENTWICKLUNG AG	Both
169	2014	AXWAY SOFTWARE SA	SYSTAR SA	Bidder only
170	2018	POOLIA AB	UNIFLEX AB	Both
171	2018	ORIOR AG	THURELLA AG	Bidder only
172	2017	INSR INSURANCE GROUP ASA	NEMI FORSIKRING AS	Bidder only
173	2014	INTERNATIONAL PERSONAL FINANCE PLC	MCB FINANCE GROUP PLC	Both
174	2016	ALPINE SELECT AG	ALTIN AG	Bidder only

175	2015	REHACT AB	FASTATOR AB	Target only
177	2017	BETSSON AB	NETPLAY TV PLC	Bidder only
178	2017	MIDSONA AB	BRINGWELL AB	Both
180	2016	FONCIERE DES REGIONS SA	BENI STABILI SPA SIIQ	Both
181	2014	PIRAEUS BANK SA	TRASTOR REAL ESTATE INVESTMENT COMPANY SA	Bidder only
183	2016	IDOX PLC	6PM HOLDINGS PLC	Bidder only
184	2016	FINANSBANK AS	FINANS FINANSAL KIRALAMA AS	Bidder only
185	2015	ASTMER INVEST SICAV SA	REMAST INVEST SICAV SA	Bidder only
187	2018	HACI OMER SABANCI HOLDING AS	CIMSA CIMENTO SAN VE TIC AS	Target only
188	2015	NATIONAL BANK of GREECE SA	NIREUS SA	Target only
189	2014	VEIDEKKE ASA	ARCONA AB	Bidder only
192	2015	SOCIETA AEROPORTO TOSCANO GALILEO GALILEI SPA	AEROPORTO DI FIRENZE SPA	Both
194	2016	XVIVO PERFUSION AB	VIVOLINE MEDICAL AB	Both
195	2015	VOLUTION GROUP PLC	ENERGY TECHNIQUE PLC	Both
196	2014	BONHEUR ASA	NHST MEDIA GROUP AS	Bidder only
198	2015	QUIXANT PLC	DENSITRON TECHNOLOGIES PLC	Both
199	2017	REWORLD MEDIA SA	SPOREVER SA	Bidder only
200	2017	GAUSSIN SA	LEADERLEASE SA	Both
203	2015	NORDIC LEISURE AB	BETTING PROMOTION SWEDEN AB	Bidder only
204	2014	APC TECHNOLOGY GROUP PLC	GREEN COMPLIANCE PLC	Bidder only
205	2015	INNOVATEC SPA	GRUPPO GREEN POWER SPA	Bidder only
207	2017	HEDEF GIRISIM SERMAYESI YATIRIM ORTAKLIGI AS	SEYITLER KIMYA SANAYI AS	Both
208	2016	KALYANI SICAV SA	CARTERA DE INVERSIONES CANARIAS SICAV SA	Bidder only
209	2015	1SPATIAL PLC	ENABLES IT GROUP PLC	Bidder only
210	2017	5EL SA	ASKNET AG	Both
211	2016	PLAYHIPPO AB	FUTURE GAMING GROUP INTERNATIONAL AB	Target only
212	2015	KARO BIO AB	MEDCORE AB	Bidder only
213	2017	INTEK GROUP SPA	ERGYCAPITAL SPA	Both
214	2017	ELBSTEIN AG	DEUTSCHE TECHNOLOGIE BETEILIGUNGEN AG	Both
215	2015	KARSUSAN KARADENIZ SU URUNLERI SAN AS	ETILER GIDA VE TICARI YATIRIMLAR SAN VE TIC AS	Both
217	2018	DEUTSCHE BALATON AG	MARENAVE SCHIFFAHRTS AG	Bidder only
218	2017	VELTYCO GROUP PLC	T4U MARKETING LTD	Bidder only
219	2018	METRO TICARI VE MALI YATIRIMLAR HOLDING AS	MEPET METRO PETROL VE TESISLERI SAN TIC AS	Both
231	2015	MUTARES AG	METSA BOARD ZANDERS GMBH	Bidder only
236	2014	TERDE INVERSIONES SICAV SA	WORLD POLICY SICAV SA	Bidder only
240	2015	PHARMA MAR SA	ZELTIA SA	Both
246	2015	TELECOM ITALIA SPA	INFRASTRUTTURE WIRELESS ITALIANE SPA	Bidder only
251	2015	SELONDA AQUACULTURE SA	DIAS AQUACULTURE SA	Bidder only
252	2015	INVERSIONES COVER SICAV SA	ACTIVOS AKRA LEUKA SICAV SA	Bidder only
253	2017	BANCO SANTANDER SA	BANCO POPULAR ESPANOL SA	Both
258	2016	ADDLIFE AB	BIOLIN SCIENTIFIC AB	Bidder only

260	2016	CARTERA BELLVER SICAV SA	INVERSIONES ESTRELLA SICAV SA	Bidder only
263	2016	AVADEL PHARMACEUTICALS PLC	FLAMEL TECHNOLOGIES SA	Bidder only
265	2017	LLUC VALORES SICAV SA	INVERSIONES ANAMARA SICAV SA	Bidder only
269	2017	CONSUS REAL ESTATE AG	GXP GERMAN PROPERTIES AG	Bidder only
272	2018	INVERMAY SICAV SA	TITULOS CUZCO SICAV SA	Bidder only
276	2018	KESKISUOMALAINEN OYJ	SUOMEN SUORAMAINONTA OY	Bidder only
280	2014	HEXAGON AB	VERO SOFTWARE LTD	Bidder only
282	2014	GEORGIA WORLDWIDE PLC	GTECH SPA	Bidder only
283	2015	KINEPOLIS GROUP NV	UTOPIA SA	Bidder only
284	2016	CARREFOUR SA	RUE DU COMMERCE SA	Bidder only
288	2016	COMDIRECT BANK AG	ONVISTA AG	Bidder only
290	2016	IWG PLC	REGUS PLC	Both

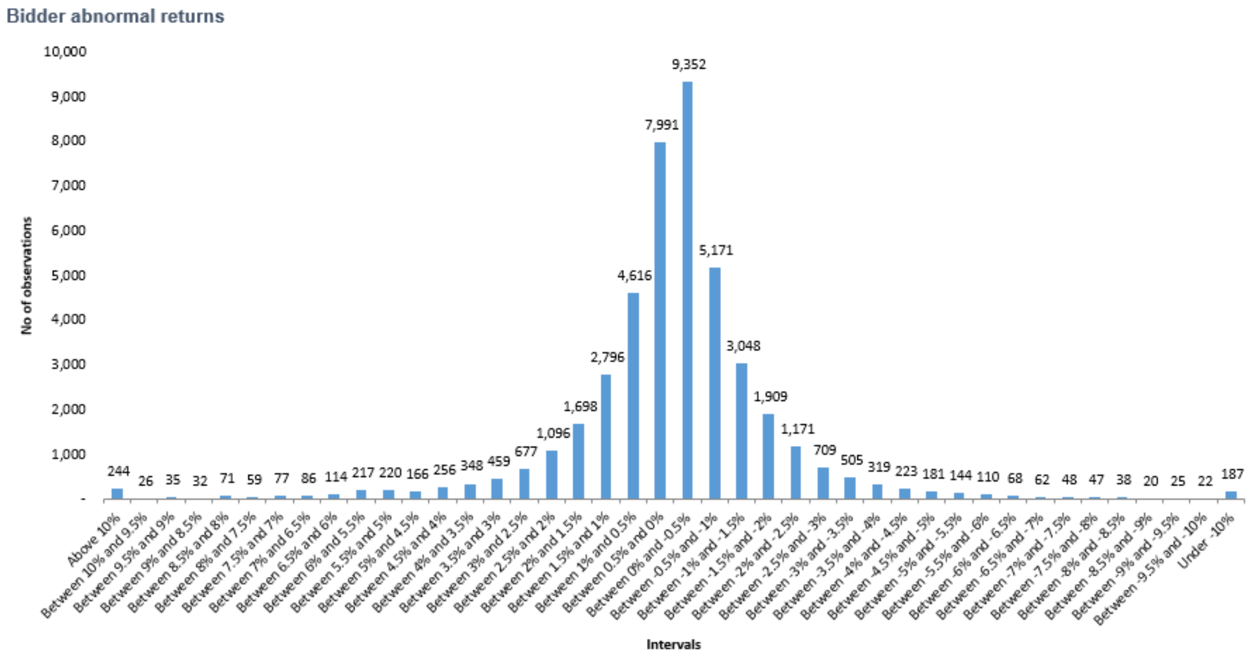
11.2 Appendix 2

List of stock indexes used as proxy for the market in each country included in the sample.

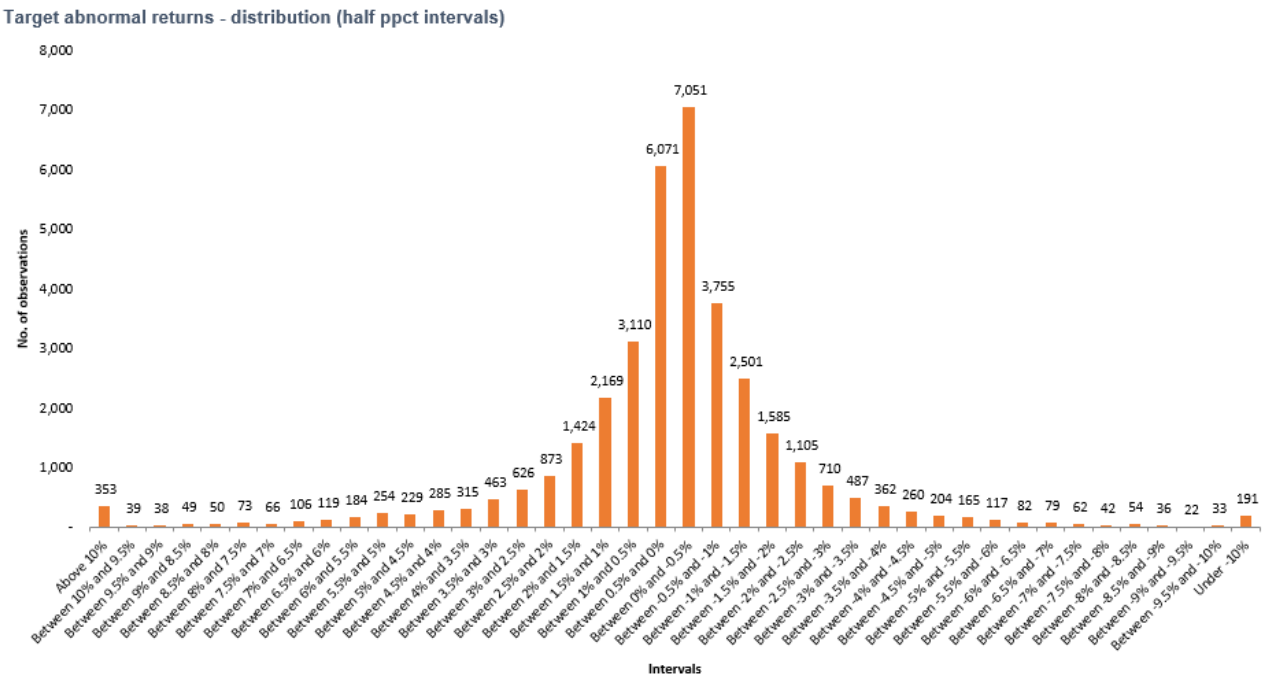
Market	Country	Stock index
GB	Great Britain	FTSE
IE	Ireland	ISEQ
DE	Germany	DAX
ES	Spain	IBEX 35
IT	Italy	FTSE MIB
FR	France	CAC 40
NL	Netherlands	AEX
BE	Belgium	BEL 20
SE	Sweden	OMX 30
LU	Luxembourg	LuxX
AT	Austria	ATX
CY	Cypress	CYSMMAPA
GI	Gibraltar	FTSE
FI	Finland	OMX Helsinki 25
CH	Switzerland	SMI
TR	Turkey	XU 100
PT	Portugal	PSI-20
GR	Greece	ASE
DK	Denmark	C25
NO	Norway	OBX
IS	Iceland	ICEX
MT	Malta	MALTEX

11.3 Appendix 3

Distribution of bidder abnormal returns



Distribution of target abnormal returns



11.4 Appendix 4A:

Hypothesis 2.1 and 2.3 CMRM-CAR regression results (Bidders)

	CMRM-CAR [-1,+1]		CMRM-CAR [-2,+2]		CMRM-CAR [-5,+5]		CMRM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.014	-0.435	-0.049	-1.341	-0.076	-1.672*	-0.109	-1.441
Stock payment	-0.023	-1.826*	-0.016	-1.117	-0.037	-2.129**	-0.065	-2.275**
Mixed payment	-0.011	-1.010	0.000	0.001	-0.002	-0.146	0.002	0.072
Bidder MarketCap	0.001	0.441	0.002	0.917	0.003	1.091	0.005	1.122
Bidder beta	-0.003	-0.339	-0.006	-0.559	-0.025	-2.043**	-0.213	-1.050
Manufacturing	0.021	1.179	0.027	1.376	0.051	2.102**	0.031	0.767
Tran., Comm. & Util.	0.003	0.148	0.018	0.782	0.041	1.409	0.022	0.461
Retail and wholesale	0.010	0.408	0.029	1.095	0.076	2.288**	0.081	1.471
Finance	0.012	0.688	0.027	1.374	0.054	2.206**	0.056	1.379
Services	-0.005	-0.252	0.002	0.077	0.015	0.586	0.010	0.223
Adjusted R^2	0.002		-0.002		0.066		0.023	
Number of observations	186		186		186		186	

****,**,* indicate signifiance level of 1%, 5%, 10%*

Source: own calculations

11.5 Appendix 4B:

Hypothesis 2.2 and 2.4 CMRM-CAR regression results (Targets)

	CMRM-CAR [-1,+1]		CMRM-CAR [-2,+2]		CMRM-CAR [-5,+5]		CMRM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	0.106	1.797*	0.118	1.859*	0.114	1.416	0.118	1.425
Stock payment	-0.082	-2.141**	-0.075	-1.807*	-0.072	-1.372	-0.073	-1.343
Mixed payment	0.026	0.790	0.028	0.809	0.021	0.470	0.008	0.176
Target beta	-0.012	-0.348	-0.030	-0.826	-0.074	-1.622	-0.082	-1747*
Manufacturing	0.079	1.353	0.084	1.331	0.084	1.051	0.104	1.264
Tran., Comm. & Util.	0.039	0.532	0.032	0.412	0.062	0.624	0.077	0.748
Retail and wholesale	-0.063	-0.914	-0.029	-0.398	0.060	0.643	0.044	0.075
Finance	-0.020	-0.340	0.014	-0.223	0.005	0.062	0.018	0.218
Services	0.037	0.636	0.040	0.641	0.054	0.684	0.072	0.878
Adjusted R^2	0.079		0.050		0.012		0.013	
Number of observations	142		142		142		142	

****,**,* indicate signifiance level of 1%, 5%, 10%*

Source: own calculations

11.6 Appendix 5A

Hypothesis 3.1 CMRM-CAR regression results (bidders)

	CMRM-CAR [-1,+1]		CMRM-CAR [-2,+2]		CMRM-CAR [-5,+5]		CMRM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.031	-0.964	-0.062	-1.7256	-0.101	-2.232**	-0.145	-1.918*
Diversifying strategy	0.007	0.746	0.012	1.103	0.014	1.046	0.011	0.488
Bidder MarketCap	0.001	0.575	0.003	1.098	0.004	1.370	0.007	1.421
Bidder beta	-0.003	-0.325	-0.007	-0.667	-0.026	-2.115**	-0.023	-1.090
Manufacturing	0.023	1.336	0.027	1.390	0.053	2.166**	0.034	0.839
Tran., Comm. & Util.	0.009	0.444	0.021	0.925	0.047	1.617	0.029	0.599
Retail and wholesale	0.008	0.347	0.026	0.966	0.072	2.134**	0.077	1.367
Finance	0.012	0.707	0.023	1.208	0.005	2.009**	0.048	1.185
Services	-0.007	-0.381	-0.004	-0.167	0.007	0.283	-0.001	-0.032
Adjusted R^2	-0.009		0.002		0.052		-0.003	
Number of observations	186		186		186		186	

****,**,* indicate signifiance level of 1%, 5%, 10%*

Source: own calculations

11.7 Appendix 5B

Hypothesis 3.2 CMRM-CAR regression results (targets)

	CMRM-CAR [-1,+1]		CMRM-CAR [-2,+2]		CMRM-CAR [-5,+5]		CMRM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	0.097	1.625	0.106	1.676	0.106	1.330	0.099	1.200
Diversifying strategy	-0.009	-0.283	0.000	0.004	-0.009	-0.224	0.000	0.006
Target beta	-0.015	-0.442	-0.034	-0.923	-0.077	-1.667*	-0.087	-1.826*
Manufacturing	0.095	1.588	0.099	1.551	0.097	1.216	0.119	1.438
Tran., Comm. & Util.	0.055	0.740	0.050	0.622	0.076	0.760	0.096	0.926
Retail and wholesale	-0.047	-0.669	-0.014	-0.184	0.074	0.789	0.059	0.614
Finance	-0.021	-0.350	-0.163	-0.251	0.004	0.054	0.020	0.233
Services	0.043	0.714	0.047	0.734	0.059	0.738	0.082	0.994
Adjusted R^2	0.033		0.014		-0.004		0.003	
Number of observations	142		142		142		142	

****,**,* indicate signifiance level of 1%, 5%, 10%*

Source: own calculations

11.8 Appendix 6A

Hypothesis 4.1 CMRM-CAR regression results (bidders)

	CMRM-CAR [-1,+1]		CMRM-CAR [-2,+2]		CMRM-CAR [-5,+5]		CMRM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.028	-0.870	-0.059	-1.616	-0.088	-1.944*	-0.133	-1.752*
Cross-border	-0.001	-0.102	-0.004	-0.346	0.011	0.780	0.013	0.540
Bidder MarketCap	0.001	0.563	0.003	1.118	0.003	1.110	0.006	1.235
Bidder beta	-0.002	-0.248	-0.005	-0.542	-0.026	-2.061**	-0.222	-1.077
Manufacturing	0.024	1.370	0.029	1.476	0.051	2.066**	0.032	0.768
Tran., Comm. & Util.	0.008	0.398	0.020	0.861	0.044	1.528	0.027	0.553
Retail and wholesale	0.010	0.426	0.029	1.082	0.076	2.252**	0.080	1.426
Finance	0.014	0.794	0.026	1.335	0.052	2.136**	0.050	1.248
Services	-0.005	-0.361	0.001	0.035	0.009	0.335	-0.001	-0.030
Adjusted R^2	-0.012		-0.004		0.049		-0.003	
Number of observations	186		186		186		186	

****,**,* indicate signifiance level of 1%, 5%, 10%*
Source: own calculations

11.9 Appendix 6B

Hypothesis 4.2 CMRM-CAR regression results (targets)

	CMRM-CAR [-1,+1]		CMRM-CAR [-2,+2]		CMRM-CAR [-5,+5]		CMRM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	0.092	1.638	0.107	1.792*	0.101	1.358	-0.022	-0.267
Cross-border	-0.021	-0.664	-0.018	-0.553	-0.044	-1.061	-0.033	-1.311
Target beta	-0.014	-0.419	-0.032	-0.877	-0.074	-1.611	-0.084	-1.096
Manufacturing	0.103	1.698*	0.105	1.626	0.113	1.3976	0.130	2.405**
Tran., Comm. & Util.	0.066	0.884	0.056	0.707	0.096	0.960	0.108	1.598
Retail and wholesale	-0.040	-0.568	-0.009	-0.118	0.087	0.930	0.068	0.980
Finance	-0.018	-0.294	-0.013	-0.200	0.012	0.146	0.025	1.528
Services	0.053	0.878	0.053	0.832	0.077	0.966	0.094	2.108**
Adjusted R^2	0.035		0.016		0.004		0.015	
Number of observations	142		142		142		142	

****,**,* indicate signifiance level of 1%, 5%, 10%*
Source: own calculations

11.10 Appendix 7A

Hypothesis 5.1 CMRM-CAR regression results (bidders)

	CMRM-CAR [-1,+1]		CMRM-CAR [-2,+2]		CMRM-CAR [-5,+5]		CMRM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.003	-0.086	-0.009	-0.222	-0.030	0.561	-0.098	-0.9837
Cash flow	0.006	0.453	0.014	1.053	0.045	3.687***	0.056	2.851***
Bidder MarketCap	-0.002	-0.679	-0.002	-0.597	-0.002	-0.527	0.000	-0.026
Bidder beta	0.028	1.819*	0.029	1.489	0.016	0.518	0.044	0.878
Manufacturing	0.020	1.297	0.022	1.196	0.043	1.632	0.034	0.685
Tran., Comm. & Util.	0.003	0.184	0.012	0.710	0.030	1.125	0.024	0.053
Retail and wholesale	0.005	0.219	0.021	0.861	0.071	1.832*	0.097	1.674*
Finance	0.007	0.615	0.014	0.998	0.045	1.901*	0.072	1.743*
Services	0.000	0.029	0.001	0.058	0.016	0.621	0.038	0.864
Adjusted R^2	0.014		0.011		0.057		0.026	
Number of observations	147		147		147		147	

****,**,* indicate signifiance level of 1%, 5%, 10%*
Source: own calculations

11.11 Appendix 7B

Hypothesis 5.2 CMRM-CAR regression results (targets)

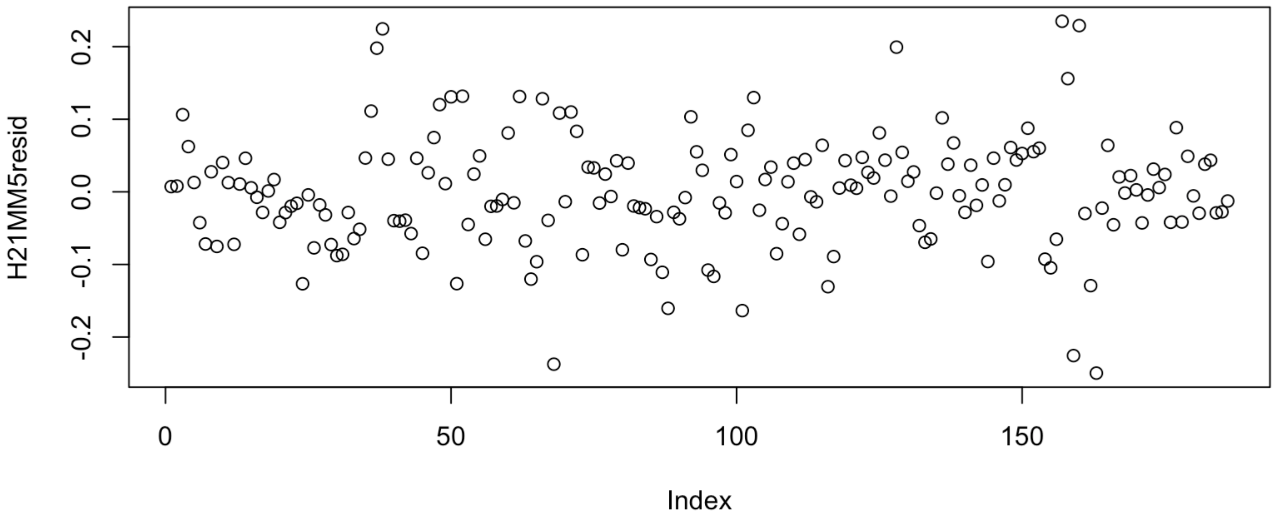
	CMRM-CAR [-1,+1]		CMRM-CAR [-2,+2]		CMRM-CAR [-5,+5]		CMRM-CAR [-10,+10]	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	0.010	0.141	-0.005	-0.072	-0.046	-0.556	-0.054	-0.636
Cash flow	0.050	0.213	0.068	0.290	0.060	0.225	0.242	0.901
Target beta	0.003	0.049	0.002	0.040	-0.025	-0.399	-0.028	-0.439
Manufacturing	0.184	2.385**	0.211	2.729***	0.257	2.960***	0.252	2.847***
Tran., Comm. & Util.	0.087	0.937	0.107	1.147	0.170	1.619	0.173	1.624
Retail and wholesale	-0.017	-0.148	-0.003	-0.027	0.045	0.344	0.000	-0.004
Finance	0.065	0.778	0.106	1.271	0.171	1.828*	0.181	1.898*
Services	0.141	1.860*	0.169	2.223**	0.210	2.461**	0.208	2.398**
Adjusted R^2	0.033		0.050		0.049		0.054	
Number of observations	81		81		81		81	

****,**,* indicate signifiance level of 1%, 5%, 10%*
Source: own calculations

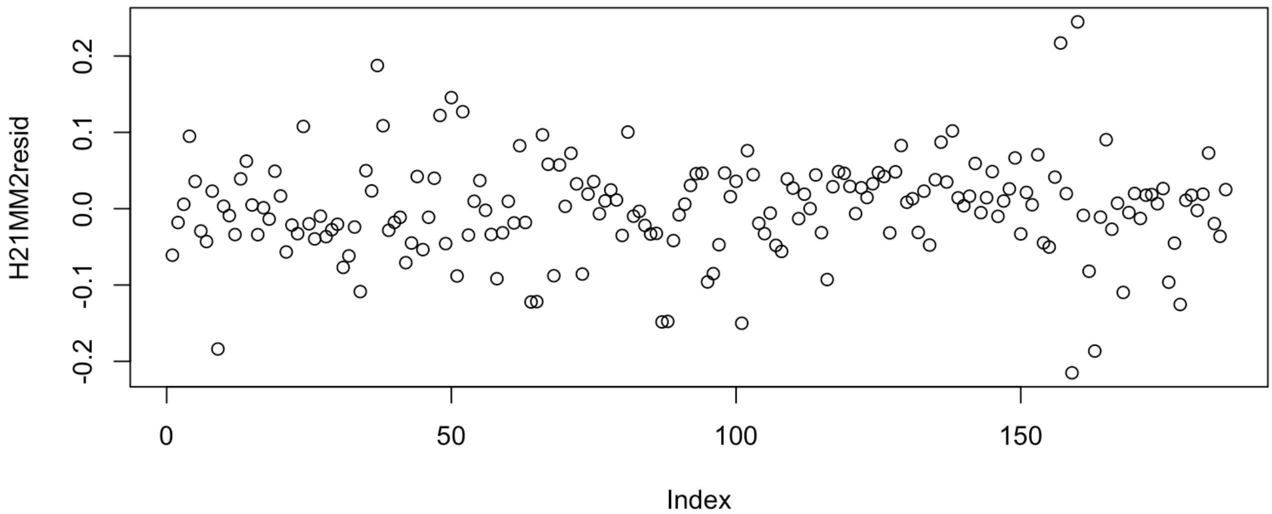
11.12 Appendix 8

Plotted residuals for Hypothesis 2.1 and 2.3 market model -5,+5 (MM5) and -2,+2 (MM2 below)
Index = number of observations.

Market model -5,+5 (MM5)
BP test resulted in p-value of 0.01339



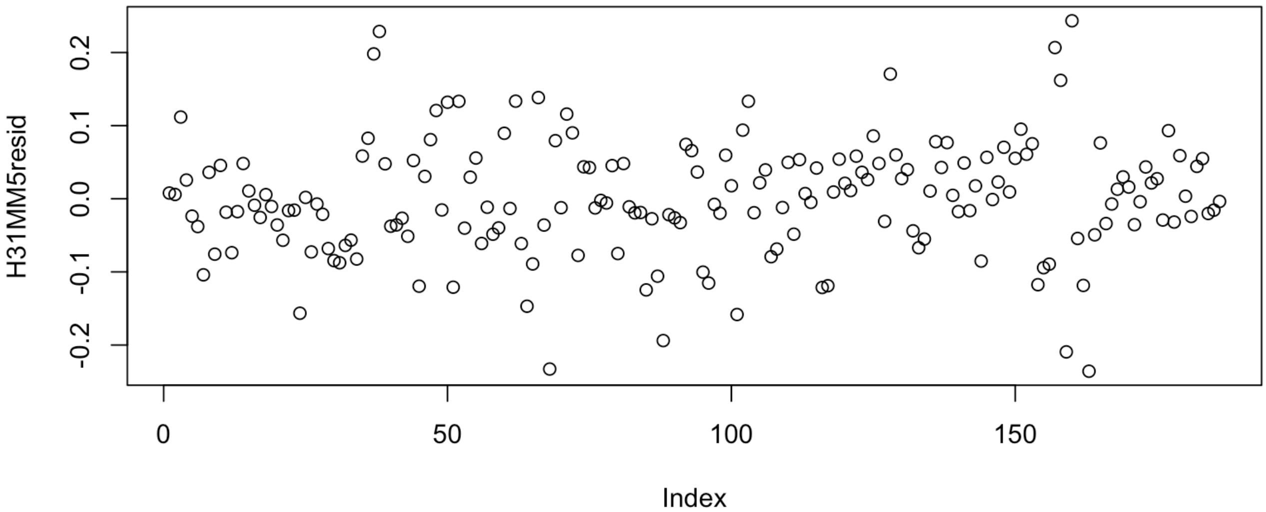
Market model -2,+2 (MM2)
BP test resulted in p-value of 0.02225



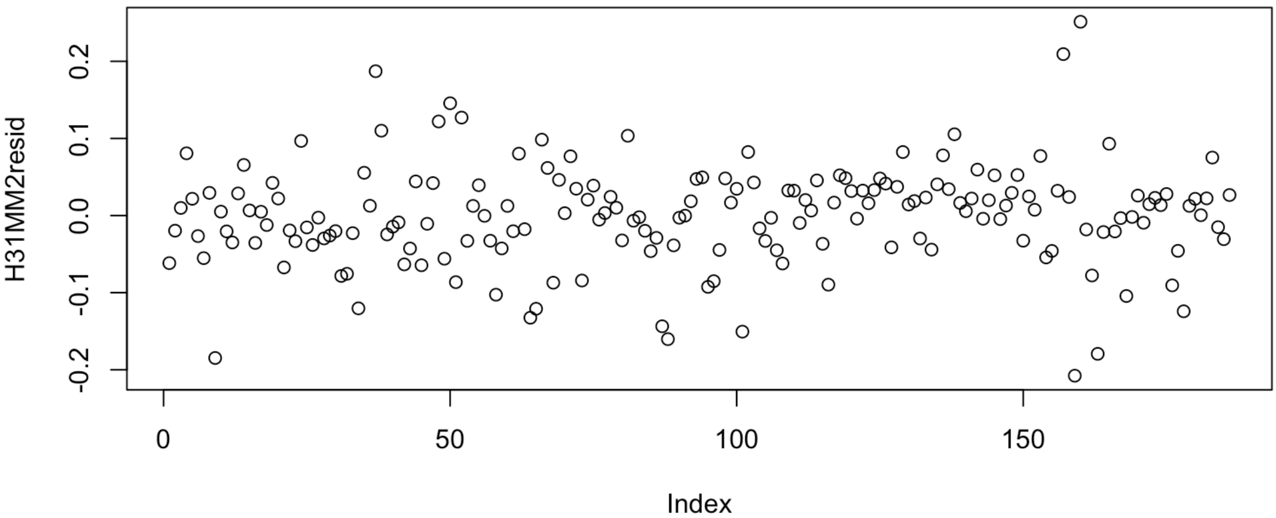
11.13 Appendix 9

Plotted residuals for Hypothesis 3.1 market model -5,+5 (MM5) and -2,+2 (MM2 below)
Index = number of observations.

Market model -5,+5 (MM5)
BP test resulted in p-value of 0.04331



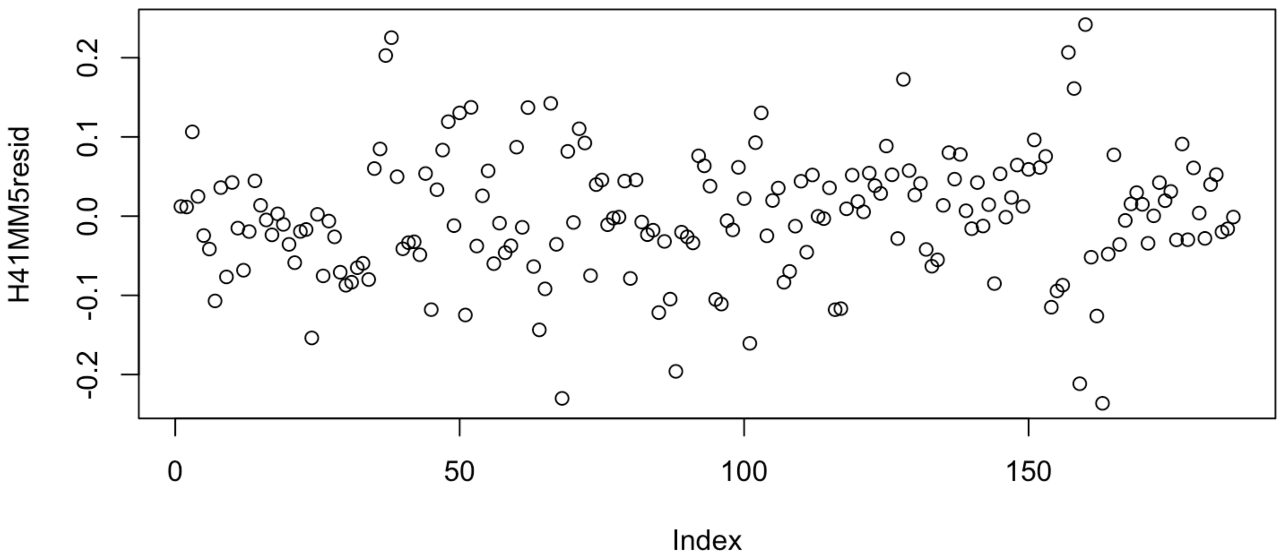
Market model -2,+2 (MM2)
BP test resulted in p-value of 0.03937



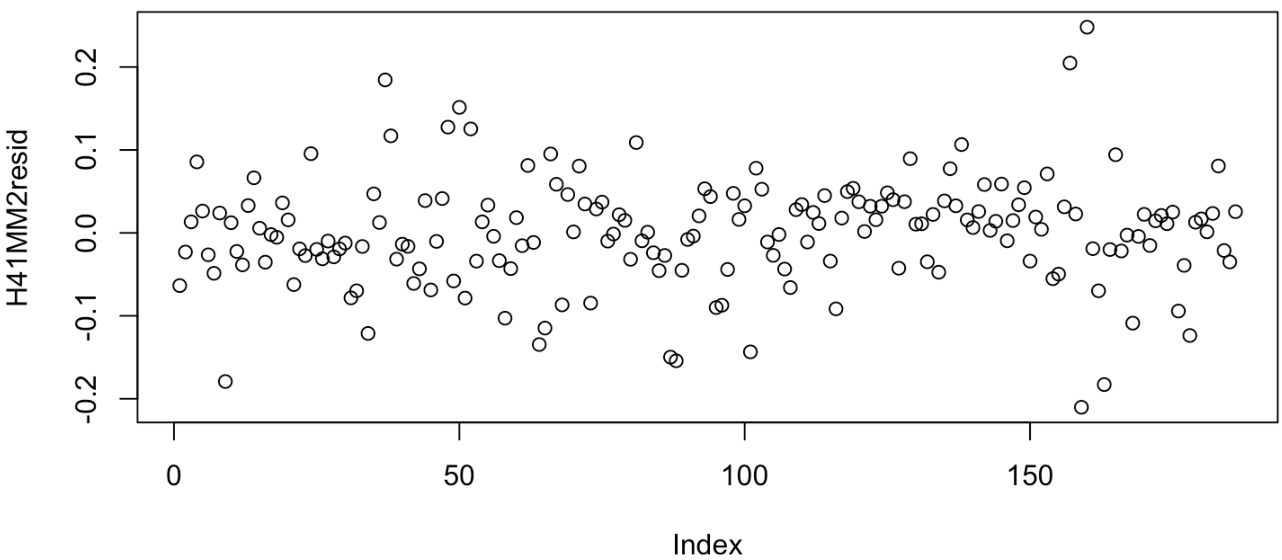
11.14 Appendix 10

Plotted residuals for Hypothesis 4.1 market model -5,+5 (MM5) and -2,+2 (MM2 below)
Index = number of observations.

Market model -5,+5 (MM5)
BP test resulted in p-value of 0.04501



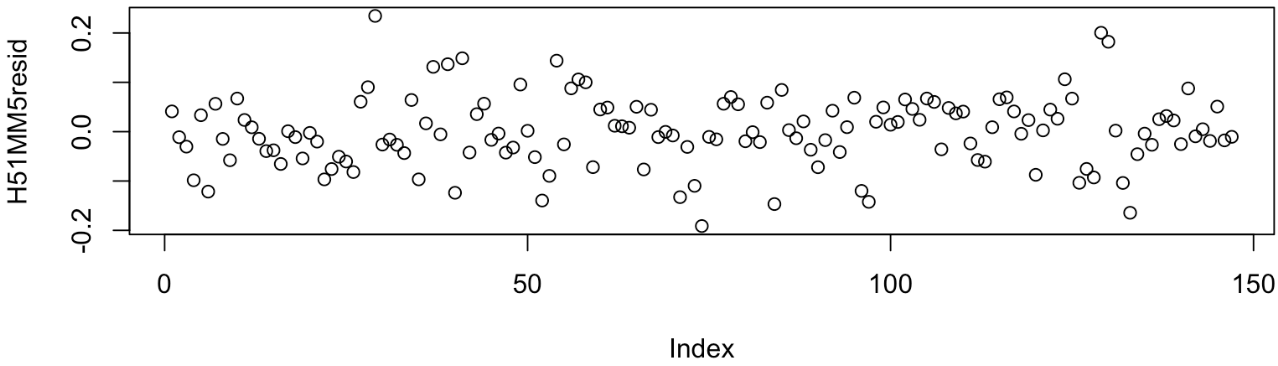
Market model -2,+2 (MM2)
BP test resulted in p-value of 0.03796



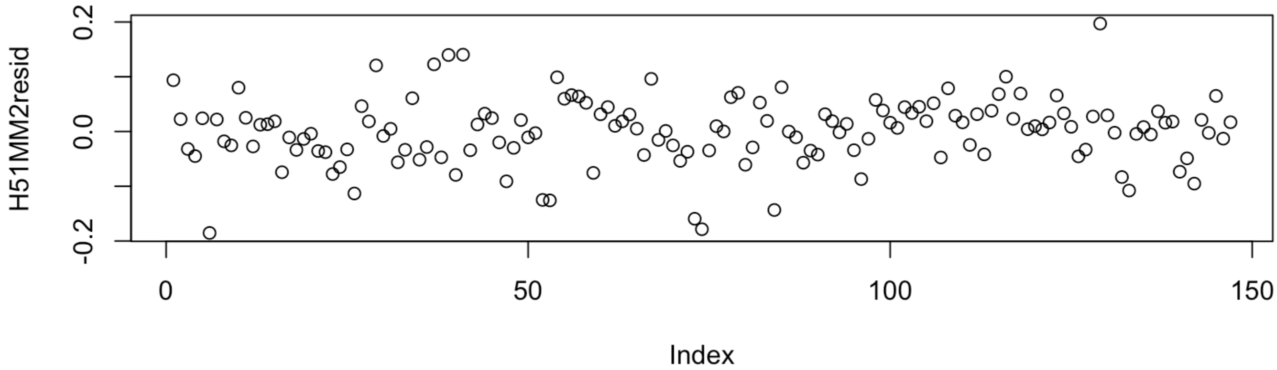
11.15 Appendix 11

Plotted residuals for Hypothesis 5.1 market model -5,+5 (MM5), -2,+2 (MM2) and -1,+1 (MM1)
Index = number of observations.

Market model -5,+5 (MM5)
BP test resulted in p-value of 0.01799



Market model -2,+2 (MM2)
BP test resulted in p-value of 0.009009



Market model -1,+1 (MM1)
BP test resulted in p-value of 0.02224