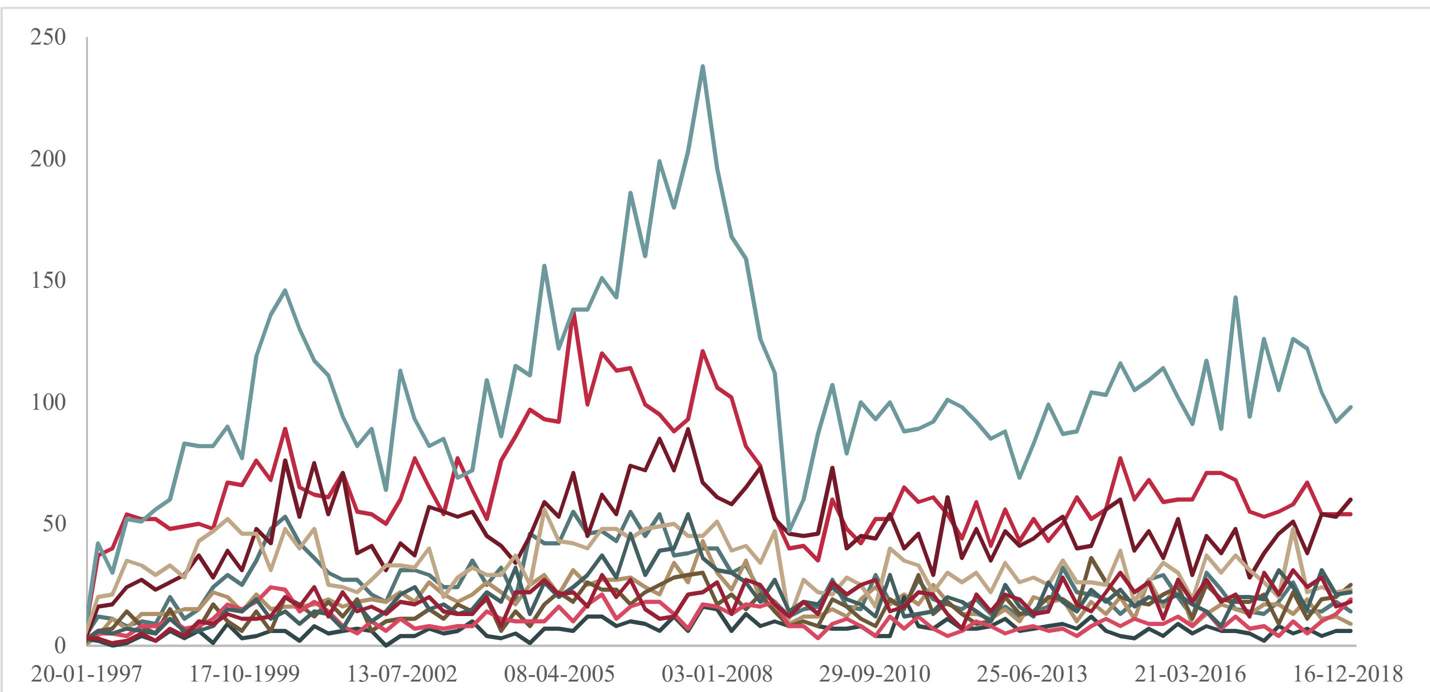
An Analysis of Industry Specific Mergers and Acquisitions in Europe between 2004 and 2018

Master Thesis

MSc. In Economics and Business Administration - Finance and Investments



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Date of submission: 16.09.2019

Total Characters: 177,676 Pages: 77.90

Executive summary

M&A activity tends to cluster over time and create merger waves. There has been proposed two different theories for this clustering. The first theory is based on neoclassical principles stating that merger waves occur as a response to an industry shock, which changes the market equilibrium. The companies within this industry will response to this industry shock by making big asset allocations, where the fastest and most cost-effective way is through mergers and acquisitions. The behavioral theory explains the occurrence of merger waves as a response to market misvaluations, which managers take advantage of and use their overvalued stock to purchase another company. This study examines how well these two theories explain the fluctuation in European M&A activity between 2004 and 2018.

A sample consisting of 115,550 mergers and acquisitions is examined. The data is divided into eleven industries and a Markov switching regime model is applied to detect the merger wave periods. Two sets of explanatory variables are tested on both the number of M&A deals within each industry but also on merger wave occurrence. The neoclassical variables include sales, employee, EBITDA, Tobin's q ration and the market-to-book ratio. The behavioral variables tested are the one- and three-year stock returns, the standard deviations of these stock returns, the market-to-book ratio and the standard deviation of this ratio. In seven of the eleven industries the neoclassical explanatory variables are the ones with the most explanatory power when it comes to both M&A deal numbers but also identification of merger waves with an average adjusted R-squared of 0.44 for the M&A deal numbers in the linear regressions and a correlation with prediction of waves of 0.73 for the merger waves in the logistic models. In multiple industries the performance of the model is increasing when both the neoclassical and behavioral variables are included, which leads to a discussion of market efficiency and whether it is more a question of how the models can be combined rather than a question of which of the neoclassical and behavioral models is the best in explaining M&A activity and merger waves.

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1. Introduction

Throughout time mergers and acquisitions (M&A) have been an important method for the expansion of business firms as they evolve through sequential stages of growth and development (Weston, Mitchell, & Mulherin, 2014). A relatively large number of published research articles conclude that M&A are not uniformly distributed, but tend to cluster over time (Harford, 2005). This is referred to as merger waves. This research is motivated by the ongoing discussion about the cause of merger waves. Generally, two theories have been discussed about the cause of merger waves, one derived from the neoclassical economics and one derived from assumptions from behavioral finance theory. The neoclassical theory explains merger waves as a response to industry specific shocks, which cause the industry to alternate (Mitchell & Mulherin, 1996). The behavioral theory on the other hand explains merger waves as a function of market misvaluation, where managers take advantage of their overvalued stocks to buy other companies (Shleifer & Vishny, 2003). Prior research has found empirical evidence in favor of both theories, but this research has tended to examine only one of the theories.

This thesis contributes to the field of study by testing both the neoclassical and behavioral hypotheses towards merger waves on the same dataset in an attempt to be able to compare the two hypotheses on the same basis. Previous studies have mainly focused on one theory, which makes it difficult to draw comparable conclusions about the theories and their performance, due to the difference in the datasets when it comes to market coverage and time period. Additionally, this study adds to the literature in terms of sample, empirical method and the explanatory variables. As opposed to previous research of merger waves, this thesis tests three different empirical methods to determine merger wave occurrence in an attempt to detect the most accurate model. Lastly this study is a conflation of explanatory variables from multiple different similar studies, chosen in an attempt to find the best performing explanatory variables. From these contributions this study is expected to add knowledge to the current understanding of the distribution of M&A deals and the M&A drivers in Europe.

1.1 Research question

The lack of comparable research and the inconsistent results as to which theoretical model has the best explanatory power towards M&A activity and merger waves trigger the motivation to examine both theories on the same dataset. This leads to the following research question:

How can traditional economic theory and behavioral finance explain the distribution of industry specific M&A deals between 2004 and 2018 in Europe?

In order to answer the research question, a couple of sub-questions will be examined:

- Which quantitative approach is best explaining the industry specific M&A distribution during the recent 22 years in Europe?
- Is it possible to empirically measure the impact of neoclassical shocks and behavioral misvaluation on the industry specific M&A activity in Europe?
- How is the European M&A activity between 2004 and 2018 empirically explained by the neoclassical and behavioral theories?

1.2 Structure

The thesis proceeds as follows. Chapter 2 will present the scientific research methodology followed by a short presentation of the terminology and historical merger waves in chapter 3. Chapter 4 and 5 presents the two tested theories on merger waves and their underlying assumptions as well as previous research examining these theories. Chapter 6 describes how the data sample is created, the tests applied to control for industry differences, the methods of identifying a merger wave, the definition of the used explanatory variables and the regressions used to examine the degree of explanatory power of the explanatory variables. Following this chapter 7 will present the results from the statistical tests and regressions and these results will be discussed in chapter 8. Chapter 9 will sum up the findings in a conclusion and chapter 10 present suggestions to future research within the field of M&A activity and merger waves.

2. Research methodology

2.1 Philosophical theory

This thesis takes its offset in positivism, where the credibility of hypotheses is considered through verification. The purpose of the study is nomothetic, which means to establish general rules for causal connections though an empirical and analytical approach and thereby create a basis for predictions. The ontological benchmark in positivism is realistic, hence it is assumed that the phenomenon and causal connections, which are studied, are occurring in the real world and independent of the researcher. The positivistic epistemology, which is a question of how we can attain knowledge, is assuming that what can be observed empirically is existing. The ideal is to reach as objective knowledge as possible, and here the empirical studies play a central role. The positivistic study has an inductive approach towards knowledge, which means it will conduct an empirical study and based on this study reach some conclusions or generate a theory. This does not mean that theories such as the neoclassical and behavioral hypotheses on merger waves cannot be used in the formulation of the research questions (Egholm, 2014). The scientist needs to be able to account for the methodology used in the study in order for another person to be able to observe the same results at another point in time. It is through this opportunity to redo a study a claim becomes verifiable (Gilje & Grimen, 1995) (Groes, Mathiesen, Fehler, & Iversen, 2019).

Previous studies have proposed the neoclassical and behavioral hypotheses as explanations to why mergers tend to cluster in waves in the US. However, there have been empirical evidence supporting both hypotheses, and hence no definitive explanation has been recognized as the most rightful explanation. This thesis takes its offset in the empirical analysis by looking into the patterns in industry specific M&As in Europe and based on this try to draw conclusions about the explanatory power of the two theories (Andersen, 2019). The aim of an empirical study is to highlight statistical associations between variables through the use of quantitative methods, which can then be interpreted analytically. The knowledge is thereby derived from actual data rather than theories.

The design of the empirical study takes it offset in similar studies on US data and the proposed theories towards merger wave occurrence. The results of the empirical study will be the basis for a discussion of the proposed theoretical hypotheses. The design of the empirical study including data collection, data processing, statistical tests and regression methods will be described in detail in chapter 6 to assure reliability of the analysis.

2.2 Delimitations

This thesis will touch upon some of the motives for engaging in M&A activity, which are related to both traditional economic theory and behavioral finance. Behavioral finance is a broad term and covers a lot of different theories as to why people make the choices they do. A lot of these theories can explain why some managers choose to engage in M&A, but they do not explain why mergers tend to cluster. Due to the focus of this thesis only the motives, which explains why mergers tend to cluster over time and which are possible to test empirically, will be examined.

The focus of the thesis is to conduct an empirical study examining the neoclassical and behavioral theories on industry specific merger wave occurrence on a broader level. Hence the study will be limited to examining the eleven classified industries empirically, and will not be studying specific shocks or one specific industry.

The datasets impose some limitations to the analysis. The empirical tests in this study is based on a dataset consisting of European M&A activity from 1997 to 2018. This time period was chosen due to limitations in the Zephyr database, which did not cover M&A deals further back than 1997. It is unknown to which extent the Zephyr database has covered the same sample population during the whole data period. If the sample size has increased over time, then an artificial increase in M&A activity will occur. The dataset covering the explanatory variables imposes additional limitations to the analysis as the quarterly coverage of the data was very limited until 2002. Additionally, even after 2004 some values are missing in the dataset, hence the calculation of the explanatory variables is affected by this to a bigger or lesser extent depending on the number of absent values. Additionally, the data used to measure the explanatory variables are limited to cover public companies due to a lack of availability and frequency of the data from private companies.

For the accounting numbers used in the explanatory variables, there might be changes in how these are calculated over the years for example due to the implementation of IFRS in 2005 (European Commission, 2019). This possible change could result in an artificial change in the numbers from one quarter to the next.

In this paper the data is divided into eleven industries. With eleven industries, the energy sector, which is the industry with the fewest deal numbers, has an average monthly deal count of 2.22 or a yearly deal count of 26.64 deals. The choice of eleven industries against for example 50 industries is a tradeoff between defining the industry groupings narrow enough to capture the industry specific impacts and to have enough datapoints in each industry grouping for the statistical models to be able to generate valid results.

The thesis is limited to look at industry classifications based on the SIC code of the target company. In approximately 97% of the M&A deals are the target and acquirer company within the same industry, hence the results of the analysis are expected to be rather similar to an analysis based on acquirer industry classification.

The analysis is also imposed by some limitations in the included explanatory variables, which can affect the sampling validity. The chosen explanatory variables are proxies for industry shocks and market misvaluations. The variables and how they are calculated are based on previous studies of the neoclassical and behavioral theories towards merger waves to assure consistency and comparability.

3. Introducing M&A

This chapter will start out with a short introduction to the relevant terminology within M&A, followed by a short review of the widely acknowledged aggregate merger waves.

3.1 M&A terminology

M&A, mergers and acquisitions, is a generic term which refers to the consolidation of companies or assets through various types of financial transactions. Mergers and acquisitions are often used interchangeably within finance studies, as they are both a potential mean in a corporate restructuring process (Sherman, 2010). M&A includes among others mergers, acquisitions, consolidations, and tender offers, which differ from a legal perspective. In general mergers refers to combining two companies into one entity through negotiations between the two companies' management and board of directors. Theoretically both companies are equal partners in the joint company. Mergers are most often friendly, as the offer is made directly to the management of the target firm. In acquisitions the acquiring company obtains a majority stake in the target company and often the target company is consumed by the acquiring company. In a consolidation a new company is created if the stockholders of both companies approve the consolidation. In tender offers, the bidding company contacts the shareholders of the target company, proposing them to tender their shares at an offer price. If enough shareholders tender their shares, it most often results in a merger, but it also occurs that the target company continue to exist. A tender offer can be conducted without the knowledge of the directors of the target company, and hence it is sometimes anticipated as a hostile takeover (Weston, Mitchell, & Mulherin, 2014). In the remaining part of this thesis mergers and acquisitions will be used interchangeably unless otherwise stated.

M&A can be classified depending on the level of relatedness between the two companies as well as on the stage of the production. Horizontal mergers include two firms operating within the same kind of business activity, whereas vertical mergers on the other hand involves firms operating within different stages in the supply chain process. Beside this, there is conglomerate mergers, which are divided into three. First there is the product extension mergers, where two companies working within related business activities merge and broadens the product lines. Next there is the geographic market extension merger, which occur between companies in related business activities but with nonoverlapping geographical areas. Lastly there is the pure conglomerate mergers which involves two companies operating within unrelated business activities (Weston, Mitchell, & Mulherin, 2014).

The payment type used in M&A differs and can involve both debt instruments, options, cash, stock, and various mixtures of these. The most common method of payment is cash, stock, or a mixture of the two. When the target shareholders receive stock, it is often referred to as a stock swap, as the target shareholders are swapping their stock in the target company for new stock in either the acquiring company or the newly created company (Berk & DeMarzo, 2017).

3.2 The history of aggregate merger waves

A merger wave is defined as "a sequence of time periods (two or more) in which the probability of a merger occurring is above the unconditional expected probability of a merger" (Rhodes-Kropf & Viswanathan, 2004). The United States had their first merger wave starting in 1897 to 1904 (Banerjee & Eckard, 2001) followed by a wave from 1916 to 1929 (Borg, Borg, & Leeth, 1989). Great Britain was the only country in Europe, which experienced a noticeable increase in M&A activity during these two waves. The US experienced a third wave between 1965 and 1969, where some of the big European countries like the Great Britain, Germany and France were involved (Berk & DeMarzo, 2017). Europe experienced its first real merger wave between 1987 and 1991 following the signed Single European Act in 1986, where the core element was to create a single market within the EU. The wave was characterized by privatization of bank, insurance and public services sectors such as telecommunication and transport. The fifth wave began in 1993 and was a global wave covering the US, Europe and Asia. The 1990s M&A were dominated by strategic and global deals, which were friendly and involved companies in related businesses. The M&As were a mean to create stronger companies, which were able to compete on a global level (Berk & DeMarzo, 2017). The fifth wave ended in 2001 when the economy entered a brief recession (Gaughan, 2012). The M&A activity resumed in 2004 with the financials market boom and ended with the financial crisis in 2007-2008 (Vancea, 2013) (Sudarsanam, 2003). Since 2009 the total value of worldwide M&A deals have increased, but it is not possible to determine if we are in the middle of a seventh wave (Szmigiera, 2019).

4. Neoclassical theory

In order to understand the motives behind engaging in M&A activities, the underlying concepts are important to keep in mind. The main concept behind the neoclassical theory is the notion of an equilibrium and that all agents are assumed be and act rational, have perfect information, are capable of prioritizing alternatives and want to maximize utility (Solow, 1994). When this is transferred to a M&A setting, only deals which increase shareholder value will occur. These value-increasing mergers are most often driven by synergies and economies of scale or scope, which is a result of the increase in firm size. The economies of scale and scope can have several dimensions including but not limited to technical and engineering relations, capacity, and specialization (Weston, Mitchell, & Mulherin, 2014).

The synergies are usually divided into two groups, cost reductions and revenue enhancements. The cost reducing synergies come from layoffs of employees with overlapping work tasks as well as elimination of redundant resources and improved production techniques, etc. The revenue synergies come from possibilities to expand into new markets, get more costumers, etc. (Berk & DeMarzo, 2017) (Bradley, Desai, & Kim, 1983) (Bradley, Desai, & Kim, 1988). One thing needs to be kept in mind, these synergies cannot create sustainable competitive advantages, hence the companies need to have a strategic fit as well. However, mergers can also be initiated even though they are value decreasing. This could be the case if the omission to acquire a company will allow a rival company to acquire the third company, resulting in an increase in the competitiveness of the rival company, which can impact the first company negatively. The first company might be in an even more unfavorably position now than if it had made the acquisition itself. Thus, an acquisition might not generate synergies, but can be beneficial from a total strategic perspective (Liu Z. , 2017).

4.1 The neoclassical view on merger waves

The neoclassical theory explains merger waves as caused by an economic disturbance to the industry. There are two somewhat related explanations as to why this economic disturbance is related to M&A activity. The first is represented by Gort (1969), who argues that the economic disturbance is causing the variance of target valuations to increase. The second explanation is among others suggested by Mitchell and Mulherin (1996), who argue the economic disturbance is forcing the companies to adapt to the new environment.

Gort (1969) argues that a M&A transaction will occur when two conditions are met; 1) a non-owner must value a target's assets higher than some of the target owners and 2) the investor surplus, given by the difference between the estimated value and the market value of the target, must be within the non-owner's budget-constraint and has to exceed the investor-surplus for every other possible investment. The discrepancies in the valuation of a company is not consistent with the efficient market under the neoclassical hypothesis. Gort (1969) argues that the discrepancies in the company valuation are a result of different expectations about future income streams and the risk associated with this income. The varying expectations is occurring as a result of an economic disturbance, which causes the future to be less predictable, which causes the variance of the target valuations to increase. The economic disturbance is assumed to affect the whole industry, and as a result the variance of the value of all industry assets will increase, and the market equilibrium will be disrupted (Gort, 1969). The market participants are assumed to react on this imbalance in order to bring the market to its new equilibrium. This hypothesis, where economic disturbances are expected to generate discrepancies in the valuation of possible target companies, can be used to explain the variation in merger rates both across time, market and industry (Gort, 1969).

The economic disturbance, also referred to as an economic shock, which causes a shift in the industry structure, can for example be a regulation or deregulation in a market, government policy, technological changes as well as of economic character such as changes in supply and demand conditions (Mitchell & Mulherin, 1996). This shift, the industry is experiencing, will often require some kind of action from the companies working within the industry in order to get the market back into equilibrium. Gaughan (2012) argues that M&A is a faster and more cost-effective way of adapting to the industry changes as opposed to organic adjustment. An example could be a sudden increase in demand, where industry members would respond by expanding. M&A is arguably the quickest way to accomplish the expansion as an internal expansion would require new employees and assets to be acquired (Mitchell & Mulherin, 1996). As all managers in the industry are expected to react on this economic disturbance at the same time, the merger activity is expected to cluster in time (Harford, 2005). Ahern and Weston (2007) argue that in the neoclassical perspective, the merger activity is dependent on the turbulence present in the economic environment, and consequently, any deviation from balance, as it is triggering a higher level of M&A activity to regain the equilibrium state.

In summery the neoclassical view on merger waves argues that shocks cause fundamental changes to affect industries or the economy as a whole. Company managers response to the shifts by reorganizing assets, which can be done through M&As. M&A are considered to be more effective as of both time and costs in the reorganization process compared to an internal reorganization, as the assets needed are already present in the target company. As a result of the reorganization of assets, the economy moves towards a new equilibrium. As all industry managers are expected to react to the shocks at the same time, mergers are expected to cluster over time.

4.2 Empirical research of neoclassical motives and merger waves

Gort (1969) is the first to document interindustry variation in M&A activity and to connect it to the economic disturbance model. Mitchell and Mulherin (1996) investigated this hypothesis in more detail. Their dataset consisted of 3,660 US firms and their M&A activity between 1982 and 1989. They found significant differences in the rate and time-series clustering of M&A activity across industries and that the M&A activity tended to cluster. Mitchell et al. (1996) examined the neoclassical approach towards merger waves with sales number, employment numbers, deregulations, energy dependence, foreign competition and financing innovations as their explanatory variables. They found that sales shocks, employment shocks, deregulations and financing innovations are significantly related to M&A activity in the US during the 80s, while the remaining variables did not have any significant explanatory power (Mitchell & Mulherin, 1996). These results are consistent with Gort's theory.

Harford (2005) conducted a similar study to Mitchell et al. (1996), and used both M&A deal numbers and merger waves as the dependent variable. Harford (2005) identified the merger waves by a random simulation procedure. Additionally, he examines both the neoclassical as well as the behavioral view on merger waves on M&A activity in the 1980s and 1990s on US data. He finds that economic, regulatory and technological shocks drive industry merger waves, hence his findings support the neoclassical view. He also examines why waves seem to be more concentrated in time than the economic shocks that prompt them. His findings suggest that there needs to be a sufficient overall capital liquidity in order to accommodate the asset reallocation. Hence for an industry merger wave to occur, both an economic motivation for the transactions and a high liquidity accompanied by relatively low transaction costs needs to be apparent. It is the macro-level liquidity component which causes the industry merger waves to cluster in time, even if industry shocks do not, and hence create an aggregate-level merger wave (Harford, 2005).

5. Behavioral theory

In most economic theory the financial markets are assumed to be efficient, including the previously mentioned neoclassical theory. This is not the case in behavioral theory. Behavioral economics studies the influence of psychology on the behavior of individuals in an economic decision-making setting. In behavioral economics not all individuals are assumed to behave rationally, have limits to their self-control, they might have non-standard preferences to the classic financial models, and are influenced by their own biases. As a result of these individuals' actions, the financial markets are unlikely to be efficient according to the behavioral theory (Cuthbertson & Nitzsche, 2004). Roll (1986) argues that M&A activity is subject to uncertainty. Under these conditions not all individuals might make rational choices. In the behavioral economics the individual might think he is maximizing overall value when he is not. This is occurring as the individual can be bounded by irrationality due to bias and limited information (Thomsen, 2008) (Hendrikse, 2003). One type of bias an individual can be subject to in connection to M&A is anchoring. Anchoring is happening when an individual uses a psychological benchmark when making a decision. In the M&A setting the manager might anchor the value of a possible target, or even his own firm, to similar firms. If the market is overvalued, the manager might not realize that the target firm is overvalued (Burton & Shah, 2013).

5.1 Principal-Agent theory

A company is most often referred to as one entity, however most companies consist of many different parties, who do not necessarily have the same interests. The shareholders for instance want their return on investment to be maximized, whereas employees care about their compensation, including salary and job security. The possible difference in interests can cause some discrepancy between the stakeholders, and this is the focus of the principal-agent theory.

In the view of the principal agent theory a company is considered as a nexus of contracts with a principal-agent relationship. A principal-agent relationship is characterized by the fact that the utility of the principal is affected by the actions of the agent. A maximization of the agent's utility does not necessarily mean that the principal's utility is maximized. Therefore, a need for a contract arises in order to govern the relationship between the principal and the agent, when a separation of ownership and management is apparent (Bergen, Dutta, & Walker, 1992). In terms of a company the shareholders are the principals and the management of the company has the role as agents. The most important aspect of the relationship is the possible conflict of interest and the asymmetric information between the principal and the agent. The asymmetries in the information arises as managers are usually better informed about the operations and opportunities of the firm compared to the owners. In agency theory irrational behavior is not the problem, it is rather the asymmetric information and differences in interests. The agent is assumed to act rationally and take advantage of superior information by optimizing personal preferences rather that shareholder preferences (Thomsen, 2008) (Hendrikse, 2003).

Jensen (1986) argues that companies, which generate a lot of free cash flow, are more prone to agency problems as the free cash flow can be allocated in several different ways including internal investment projects, acquisitions and dividends or share buybacks. When a company has more free cash flow than it needs for its daily operation, it should be spent on whatever maximizes the value from the perspective of the shareholder. Jensen (1986) argues that this is not always what happens, as the managers might go against the wishes of the principals, and instead act in the interest of their own financial or personal best.

It is a well-known fact that the size of the company matters in several ways. Robin Marris (1964) showed that managers' pecuniary and psychic incomes were linked to the growth of the firm they were managing. This arises as many managers find it more prestigious to manage a large company (Brealey, Myers, & Allen, 2008), the pay of a manager is often positively correlated with the company size, and the risk of the company ending up as a target themselves declines with company size. If the company is acquired, the management of the company will often experience either a loss or degrading in position, and hence the bigger the company the less risky is the position of the management (Thomsen, 2008). As a result, managers' utility can be expressed as a function of the company's growth. This is also referred to as empire building. This empire building can be done either by internal or external growth, where Mitchell et al. (1996) argues that M&A is the fastest and most cost-effective way to grow a company.

5.2 The behavioral view on merger waves

When the market is not efficient, there will be times where the market is optimistic and times where it is pessimistic, and as a result times when the market is overvalued and times when the market is undervalued (Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012). Multiple theories have been proposed as to how these changes in the market can affect the occurrence of merger waves.

In behavioral theory managers are expected to undertake wealth-generating mergers, but also wealth-destroying mergers if these provide private benefits to the managers. In an efficient market the value of the acquiring company should fall by the amount of the wealth to be destroyed, when the merger is announced. Managers is expected to avoid these wealth-destroying mergers if markets are efficient, as there would be an immediate and negative response to the acquisition announcement. Gugler et al. (2012) assume that the capital market is not strongly efficient, and as a result a wealth-destroying merger will not necessarily cause the acquirer stock to decrease. As described under the principal-agent theory, managers get utility from the growth of the company they are managing either financially through pay or the personal gain from managing a larger company. When there is over-optimism in a market, the stock prices most often rise, creating a boom. Gugler et al. (2012) argue that in periods of over-optimism the number of wealth-destroying mergers will increase, as managers anticipate a favorable reaction by the market to the announcement of a merger. If multiple companies take advantage of the over-optimism, a merger wave can occur (Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012).

Shleifer and Vishny (2003) also assumes that the financial market is inefficient and hence misvaluations appear. Additionally, they assume that managers are rational and know the perceived value of synergies, the long-run valuation of their company and understand stock market inefficiencies. Managers seek to maximize their personal wealth. As a result, merger waves occur when deviations between the market and the fundamental value appears and when managerial incentives of both the acquirer and target coincide (Shleifer & Vishny, 2003). Shleifer et al. (2003) argue that their theory helps explain which companies participate in M&A activity, the method of payment, and merger waves by using the relative valuations of the combining firms. They argue that when a company's stock is overpriced, management will use stock as payment method in M&A and use cash otherwise, as long as management is better informed about the prospects of the company than the market is. In periods where the market prices are higher than their intrinsic values, the market for corporate control may provide an efficient mechanism for resetting values. An overvaluation of a company's equities gives access to cheap capital on the short run. This overvalued equity can be used to make "cheap" acquisitions paying with the overvalued stock. Due to the dispersion in valuations, less overvalued targets can also be covered by this model (Harford, 2005). The takeover activity can continue until the stock prices return to their intrinsic values. On a large scale this can lead to a merger wave (Jensen, 2005).

According to Rhodes-Kropf and Viswanathan (2004) the misvaluation in the market consists of two components, a shared market-vide component and an individual firm-specific component. The rational target knows whether their own company is overvalued or not, but they do not know where the misvaluation comes from, whether it is a market effect, sector effect or firm effect. Hence when the management in a target company has to consider an acquisition offer, they have to base the decision on its assessment of the possible synergies and their own private information. Here the target can be subject to anchoring. Rhodes-Kropf et al. (2004) assumes that the management in a possible target company will accept a purchase offer if the offer is higher than the standalone value of the company. They further argue that when the market-wide overvaluation is high, the error in the estimated synergies will be high as well. As a result, the target company is more likely to overestimate the synergies when the market is overvalued, and hence more likely to accept the offer, as they will underestimate the shared component between target and acquirer of the misvaluation. From this follows that mergers are more likely to occur when markets or sectors are overvalued (Rhodes-Kropf & Viswanathan, 2004). The model of Rhodes-Kropf et al. (2004) differs from that of Shleifer et al. (2003) in that the target managers rationally accept the overvalued equity because of imperfect information about the misvaluation components rather than the target management having a short time horizon, as Shleifer et al. (2004) argues.

As all the theories rely on temporary misvaluations in the market and also on high variation in the valuations, they are all grouped under one as the behavioral hypothesis on merger waves.

5.3 Empirical research of behavioral motives and merger waves

Rhodes-Kropf, Robinson and Viswanathan (2005) tests the hypothesis set forth by Rhodes-Kropf et al. (2004) by breaking the market-to-book (MB) ratio into three components; the firm specific pricing deviation from short-run industry pricing, the industry-wide and short-run deviations from the firms' long-run pricing and long-run pricing to book. They find that the MB ratio between acquirers and targets is large and mainly driven by the firm-specific error, with the acquiring companies being priced significantly higher than the target companies. Furthermore, they find that both the acquirer and target tend to cluster in sectors with a high time-series error, implying that they share a common misvaluation component. Summed up, in industries, which are overvalued, overvalued companies tend to buy less overvalued companies. However, Rhodes-Kropf et al. (2005) find that only 15% of the merger activity at the industry level is explained by misvaluations. The misvaluation plays an important role when it comes to who buys whom and how are they going to finance the acquisition. Rhodes-Kropf et al. (2005) used the MB ratio to explore misvaluation empirically on their dataset covering the years 1984 to 2001, and found strong support for the idea that misvaluation shapes merger activity (Rhodes-Kropf, Robinson, & Viswanathan , 2005).

Gugler, Mueller and Weichselbaumer (2012) argue that if the neoclassical hypothesis holds, then both listed and unlisted companies should experience waves. In their empirical analysis they find significant differences between listed and unlisted companies, which speaks in favor of the behavioral hypothesis. They also find that the peak of merger waves coincides more or less with the peaks of stock market booms, which they argue speaks in favor of the behavioral hypothesis. Gugler et al. (2012) conduct their research on a dataset covering year 1991 to 2004 and compares data from the United Kingdom with data from continental Europe.

Gugler et al (2012) present evidence linking merger activity to measures of optimism in both equity and bond markets. This market optimism is an offsetting factor to merger waves according to the stock overvaluation and managerial theories. Among other things they find that shareholders of acquiring companies get significantly lower returns when a M&A deal is undertaken during optimistic market conditions compared to M&A deals undertaken when market conditions are more normal. This is not only the case for overvalued firms, but occurs when there is optimism in the equity and bond markets. This speaks in favor of the managerial theory (Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012).

Lastly Harford (2005) also examines the behavioral hypothesis alongside the neoclassical hypothesis. He uses the MB ratio, the three-year stock returns, and the standard deviation (sd) of this stock return as proxies for overvaluations in the market. He finds that the MB ratio has some significant explanatory power on both dependent variables; a dummy stating the start of a merger wave and aggregate merger activity. The other two variables do not have any significant explanatory power. However, when both the neoclassical and the behavioral variables are added at the same time, the MB ratio is no longer significant. Harford's (2005) results hence supports the neoclassical theory.

6. Analysis Methodology

This chapter will describe the analysis methodology covering the data collection and filtering, the statistical tests made to check for differences in the industry data, followed by a description of the methods used to identify merger waves and lastly a presentation of the explanatory variables and regression types. For all statistic tests made in the thesis a significance level of 0.05 will be applied unless otherwise stated.

6.1 Data collection, dataset description and filtering, data pre-processing

The analysis in this thesis is based on structured data from Zephyr, which is a database collecting a comprehensive amount of data about various types of M&A deals dating back to January the 1st 1997 and up until today, with a total of 1,859,708 deals. The database covers M&A activity from all across the world. The data was filtered generating a dataset consisting of all announced, completed, unconditional or pending mergers and acquisitions recorded by Zephyr between January the 1st 1997 and February the 28th 2019 with a minimum deal value of $10 million. The Zephyr dataset does not go further back than January the 1st 1997 but still some deals with an announcement date in 1996 appears. This occurs as the date restriction concerns the completion date, whereas the announcement date is used as filtering in this paper. The announcement date is used as opposed to the completion date as it will be closer in time to a possible triggering event. The deals with announcement date in 1996 have been removed, as they provide an insufficient picture of the deals made in 1996. A deal type filter was applied to the data in order to remove deals such as IPOs and Private equity deals as these are assumed to depend on other explanatory variables than mergers and acquisitions. Afterwards the current deal status filter was applied to remove rumors and cancelled deals. The time period filter is used to ease the analysis by not working with half months of data as the monthly data will otherwise not be directly comparable. At the end a minimum deal amount was applied to avoid small "insignificant" deals. These smaller deals are assumed to be distributed more evenly over time, as they do not have as big an impact on the acquiring firm's finances as a bigger and more expensive deals have (Weston, Mitchell, & Mulherin, 2014). The described filtering resulted in a total of 115,550 deals in the dataset. The filtering and the subsequent deal counts are displayed in figure 1.


SEARCH STRATEGY — Add a search step | Alert me | Save | Clear all steps

SEARCH STRATEGY	Step result	Search result
1. All deals	1,859,991	1,859,991
2. Deal type: Acquisition, Merger	696,283	696,283
3. Current deal status: Announced, Completed, Unconditional, Pending	1,618,750	569,966
4. Time period: on and after 01/01/1997 and up to and including 28/02/2019 (completed-confirmed, completed-assumed, announced)	1,631,899	569,046
5. Deal value (m USD): min=10 (including estimates)	463,462	115,550

Boolean search: 1 And 2 And 3 And 4 And 5 — Refresh — TOTAL : 115,550

Figure 1: Data filtering and deal numbers

For each deal the variables included are announcement date, target country code, target SIC code, and acquirer SIC code. SIC stands for Standard Industrial Classification, and is a four-digit number, which can be grouped into broader or more narrow industry groups. In this thesis eleven sectors or industries will be used based on the Global Industry Classification Standard (GICS) (MSCI, 2019). These eleven industries are listed in appendix 1. It should be noted that not all of the companies involved in a deal have a SIC code assigned, just as some of the companies have multiple SIC codes assigned, as they work within multiple areas.

In addition to the structured data from Zephyr, data is needed for the explanatory variables. The data used to compute the explanatory variables are total book assets, book equity, market value, sales numbers, number of employees, EBITDA margin, and adjusted stock closing prices. This data was collected from FactSet, and includes the mentioned variables for STOXX Europe 600. The STOXX Europe 600 index includes 600 companies from 17 European countries, countries which are all included in the M&A deal dataset (STOXX Ltd, 2019). The countries represented with the most companies in the index, are also the companies which have the most M&A deals, for example Great Britain, Germany and France. The index covers both small, mid and large capitalization companies within different industries. The companies included in the index is revised every quarter and the company list therefore changes from time to time. The list was pulled on July the 15th and the explanatory variables are therefore based on the data from the 600 companies included in the index at this point in time. What needs to be noted is that the index only covers public companies, and the private companies are therefore not represented in the calculations of the explanatory variables. This exclusion of the private companies results in some bias to the data. All of the explanatory variables are calculated as margins in an attempt not to give too much weight to the biggest companies and their increase or decrease in the variables. To be able to compare the accounting numbers over time, some of the variables were adjusted for the consumer price index (Federal Reserve Bank of St. Louis, 2019), which measures the changes in the price level.

The data needed for the explanatory variables were almost impossible to find for private owned companies, as most countries have different requirements to the financial reporting when it comes to privately owned companies compared to publicly owned companies. Some databases provide accounting numbers for privately owned companies, but the reports are very insufficient and most of them does not go further back than 2014. Additionally, the lower requirements to the reporting of private companies mean that these companies rarely report on more than a yearly basis, hence quarterly numbers were only available for a very limited number of companies.

Another thing that should be noted is that only a limited number of companies have quarterly data back to 1995. Therefore, the data for the explanatory variables were collected on a quarterly basis from 2002 up until 2018. This choice was made due to the very limited number of quarterly numbers (up until 1999 there were no more than 50 recordings per month out of 600 per variable) as the variables were not assumed to represent changes to an industry but rather changes in a limited number of companies. The fact that the companies in the index changes over time also mean that the company list might include companies, which were not listed in 1994 or maybe did not even exist, and therefore some of the values used in the explanatory variables are not accessible in the beginning of the time period.

6.1.1 Data pre processing

The first step in the data pre-processing was to combine the deal data from Zephyr with the GICS industries. The primary US SIC code for the targets were translated into an industry denoted by the numbers 1 to 11. If a company have several SIC codes, but they lie within the same industry, the deal counts as one. If a company's multiple SIC codes belongs to different industries, then a deal will be registered in both industries. This is a result of some limitations in the dataset as it is not registered, which industry is the primary one. In the dataset the target companies are on average registered within 1.02 industry sections whereas the acquiring companies are on average registered within 1.03 industries.

As previously mentioned initially the dataset contained 115,550 deals. After dropping transactions where the target's SIC code were not identified (255 deals) and deals where the country registration was not identified (1,121 deals) the final target dataset consisted of 114,174 registered deals. The target firms originate from 195 different nations across the world. After removing all non-European targets 32,385 deals were remaining. The European industry deals are displayed in figure 2 below.

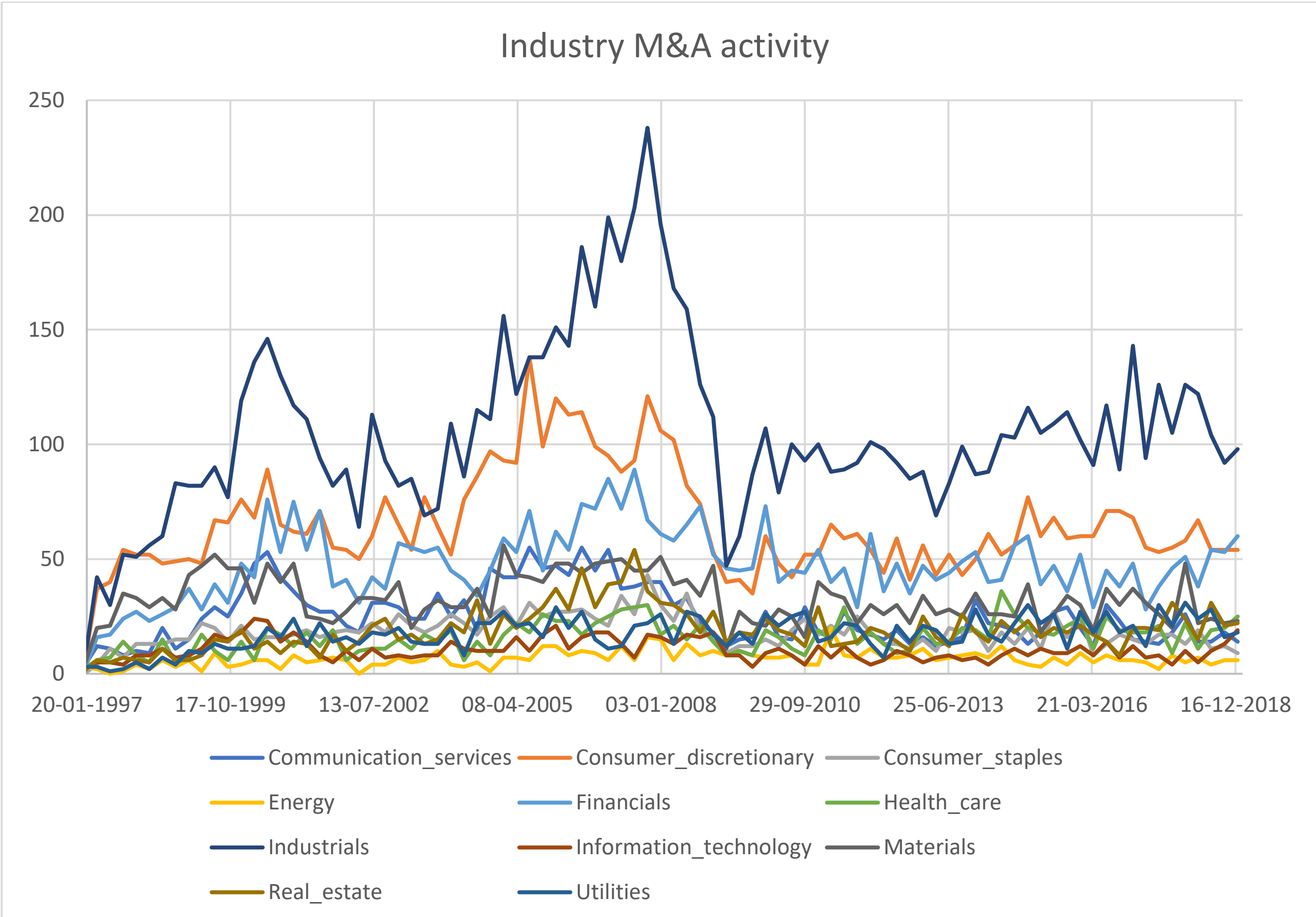

Figure 2: Industry M&A activity

6.2 Data analytics: Modeling, methods and tools

6.2.1 M&A activity across time and industry

The first steps in the data analysis is to access whether there is an actual variation in the merger activity across the eleven industries, indicating whether it is industry specific or aggregate explanatory variables, which should be tested for explanatory power.

6.2.1.1 Differences in the rate of M&A activity

In this subsection the dispersion of the M&A data will be analyzed through the variances. The variances are used to examine whether the variation in takeover and restructuring activity is significant across the different industries. If there is a significant variation in the M&A activity across the industries, it suggests that some industries might have experienced what we classify as M&A waves during the sample period. A statistical approach to this question is to test the equality of variances (Baesens, 2014). This is tested both on monthly and quarterly deal counts for the 11 industries. For the quarterly deal counts the 2019 data is removed prior to the statistical analysis, as only two months of data is available due to the time of the data collection. There are several tests for the equality of variance including Fisher's F test, Bartlett's test, Levene's test, and Fligner-Killeen test. Which of the tests to use depends on how many groups that need to be compared and also the distribution of the data. Fisher's F test is restricted to comparing two variances, hence it is not suitable here. The other three tests can compare k variances. The Bartlett test has the best performance if the data has a normal distribution. Levene's test is an alternative to the Bartlett test, and is less sensitive to departures from normality. Lastly the Fligner-Killeen test does a similar job, but performs better than the other two when the data is non-normally distributed. To pick the most suitable test, the data should to be tested for normality. This will be tested both by creating a histogram with a density curve, creating a quartile-quartile plot (Q-Q-plot) and lastly applying the Shapiro-Wilks test. The histogram and the Q-Q plot are used for checking the normality visually. If the data follows a normal distribution, then the histogram will create a bell shape. A Q-Q plot compares two probability distributions, here the distribution of the data and a normal distribution, by plotting their quantiles against each other. If the data is normally distributed, the points in the Q-Q plot will lie on the line $y = x$ (Cuthbertson & Nitzsche, 2004). The Shapiro-Wilks test calculates a W statistic;

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Where $x_{(i)}$ are the ordered sample values and a_i are constants which are generated from the means, variances and covariances of a n size normally distributed sample. The W test is meant to provide an index or test statistic which can be used to evaluate the supposed normality of a sample (Shapiro & Wilk, 1965).

From figure 2, the data does not seem to be normally distributed. If this is confirmed by the plots and Sharpiro-Wilks test, the Fligner-Killeen test will be applied to the data to test the equality of variances across the industries and markets.

For the Fligner-Killeen test the null hypothesis is that all industry variances are equal, hence the alternative hypothesis is that at least two of the variances differ. The test uses the median in a simple linear rank method where the ranks of the absolute values of the centered samples and weights are used. The Fligner-Killeen test uses the chi square test statistic given by:

$$\mathrm{X}^2 = \sum \frac{(f_o - f_e)^2}{f_e}$$

Where f_0 is the observed value and f_e is the expected value. As the formula shows, the chi square statistic is based on the differences between what is observed in the data and what would be expected if there were no relationship between the variables (Sharpe, De Veaux, & Velleman, 2014) (Fligner & Killeen, 1976).

6.2.1.2 Differences in the timing of M&A activity

Besides from looking at the variances in the dataset, examining the industry differences in the timing of M&A activity can tell something about the possible clustering properties. This can be done by performing an analysis of variance (ANOVA) of the interindustry variation in the mean takeover date. The classic ANOVA assumes that the data is normally distributed and that the group variances are homogenic. The variation in the graphs in figure 2, could indicate that the variances are not the same across the different industries. Whether this is true is tested in the section above. If the assumptions hold, the classic ANOVA test will not be applicable. Instead the Welch's ANOVA, which also tests for the equality of group means, can be applied, as it can be used even when the variances are not homogenous. However, the Welch ANOVA assumes, just as with the classic ANOVA, that the data is normally distributed. The deal data is not assumed to be normally distributed, but the Welch ANOVA might still be applicable due to the central limit theorem (CLT). According to the central limit theorem the sampling distribution in large samples tend to be normal, regardless of the shape of the data and the means of random samples will tend to have a normal distribution, regardless of the distribution (Ghasemi & Zahediasl, 2012) (Analyse-it, 2019) (Sharpe, De Veaux, & Velleman, 2014). The main idea behind the Welch's F-test is to reduce the effect of heterogeneity by using weights. The test statistic is stated in appendix 2 (Liu H. , 2015).

To be able to examine the mean takeover time each deal is assigned a number depending on the announcement month. Hence an announcement in January 1997 = 1, February 1997 = 2, … , December 2018 = 264. The null hypothesis for Welch ANOVA is that the mean is the same for all groups. A two-sided test is applied, hence the alternative hypothesis is that the mean of at least one sample is not equal to the others. If the null hypothesis is rejected, it indicates significant variation in the timing of M&A activity across industries.

In addition to the Welch ANOVA test the Kruskal-Wallis test will also be applied. This test is used to compare two or more samples for statistically differences between the samples. It is a nonparametric test, meaning there is no requirements to the data distribution. The test statistic approximates a chi-square distribution with $k - 1$

degrees of freedom. The reason behind running both tests is that the Kruskal-Wallis test is not as powerful as the ANOVA test, but it does not assume normality in the data distribution. The null hypothesis of the Kruskal-Wallis test is that the groups are from identical distributions and hence the alternative hypothesis is that at least one of the groups is from another distribution (Statictics Solutions, 2019). If the p-value is below the chosen significance level of 0.05, the null hypothesis can be rejected and hence there is a significant difference between the groups. The test statistic is stated in appendix 3 (Liu H. , 2015).

6.2.2 Identification of waves

From figure 2 it is readily apparent that at least some industries experience periods of high M&A activity followed by periods of lower M&A activity. However, to rigorously establish that waves do in fact occur, a statistical method has to be incurred. In the existing literature several different approaches have been used to identify merger waves including simulating the occurrence of the M&A deals (Harford, 2005), detrending the monthly number of M&A by removing the best straight line fit for the month in question and the previous five years (Doukas & Zhang, 2016) and by employing a switching model (Gugler, Mueller, & Weichselbaumer, 2012). The three approaches will be described below and tested in chapter 7.2.1.

The simulation method is described in detail in appendix 4, but is shortly explained making a monte Carlo simulation of the distribution of the M&A deals. If the actual data is experiencing a wave is determined based on the highest M&A deal peaks in the simulations. The simulation method requires the researcher to decide on a specific period of time for the waves to last, as an example Harford (2005) uses two years. The two year period is chosen based on a paper written by Mitchell et al. (1996), who writes: "While the choice of a two-year window is somewhat arbitrary, alternate groupings (e.g., a three-year period) yield similar conclusions." (Mitchell & Mulherin, 1996, s. 205-207). Hence there does not seem to be any statistical justification for using two years rather than for example three years. Furthermore, the data sample should be divided into subperiods when it covers multiple decades of data. This is done in an attempt to take the timely increase in the mean into account. These splits are a subjective decision and can for example be based on the occurrence of aggregate merger waves.

In method two the best five-year straight-line fit is removed from the data. This has the implication that it is not possible to tell whether there were any M&A waves during the first five years (1997-2001), as M&A deal data for the preceding five years is not accessible from the used data source. There is no specific reasoning behind using five years rather than four or six years for the straight line.

Town (1992) looks at the time-series of M&A and finds that a switching regime model, also known as the Markov switching model, characterizes the time-series better than a conventional ARIMA model. A switching-regime model allows the data to be in two or more states, also called regimes. For the purpose of this analysis two states will be used, a state of high M&A activity (wave period) and a state of low to moderate M&A activity (non-wave period). Town's model is based on Hamilton's work from 1989, where he is using a Markov switching-regime model to describe the business cycle. Hamilton (1989) likewise found that the business cycle is more accurately characterized by a recurrent pattern of shifts between two states, a recessionary state and a growth state, than by traditional linear models. Town (1992) found the nonlinear state dependent structure of Hamilton's model appealing to apply to the M&A data (Town, 1992) (Hamilton, 1989).

The Markov switching model is combining two or more dynamic models through a Markovian switching mechanism. The Markov model allows to relax the often-used assumption about a constant mean and variance in a time series, assuming stationarity. With the Markov switching-regime model parameters such as mean and variance can be different across the states and hence different equations and structures characterize the time series behavior in the different regimes.

Hamilton (1989) uses the Markov switching model to characterize the changes in the parameters of an autoregressive process. An autoregressive (AR) model predicts the future behavior of a dependent variable (y) based on the past behavior of the dependent variable. The number of lagged y values used as explanatory variables determines the order of the autoregressive model. For example an AR(1) model is a first order autoregressive process which at a point, t, depends on the value of y at time t-1. An AR(p) model is defined by the equation:

$$y_t = \mu_{s_t} + \phi_1(y_{t-1} - \mu_{s_{t-1}}) + \phi_2(y_{t-2} - \mu_{s_{t-2}}) + \cdots + \phi_p\left(y_{t-p} - \mu_{s_{t-p}}\right) + \varepsilon_t$$

y_t is the dependent variable, μ_{st} is the state-dependent process mean, $s_t = 0 \; or \; 1$ denotes the unobserved state of the system and $\varepsilon_t \sim N(0, \sigma^2)$ i.e. white noise. The Markov switching-regime model will be testing using AR models of order 0, 1 and 2 (Hamilton, 1989).

The Markov switching model applies a switching mechanism, s_t, which allows the parameters in the AR process to change within the different regimes. The regimes are unobserved and the process can switch among the regimes throughout the sample period. The persistence of each regime is determined by the transition probabilities where the switching mechanism is controlled by an unobservable state variable, which yields random and frequent changes between the regimes. The switch between regimes or states is governed by the outcome of a first-order Markov chain. This means that the probability of a change in regime only depends on the value of the most recent regime. The switching mechanism s_t is not observed directly but we can make an inference about the value of s_t based on the observed behavior of y_t. The inference will be in the form of two probabilities, p and q.

$$Prob[S_t = 1|S_{t-1} = 1] = p$$

$$Prob[S_t = 0|S_{t-1} = 1] = 1 - p$$

$$Prob[S_t = 0|S_{t-1} = 0] = q$$

$$Prob[S_t = 1|S_{t-1} = 0] = 1 - q$$

As a result, the regime classification in this Markov switching model is probabilistic and determined by data. The parameters affecting y_t are the variance of the Gaussian innovation σ^2, the autoregressive coefficient ϕ, the intercepts and the two transition probabilities, p and q. The parameters are found though maximization (Hamilton, 2005).

From a technical point of view the test is performed in R. At first an ordinary least squares (OLS) regression is performed followed by the msmFit function in R, which is an implementation for modeling Markow Switching Models using the EM algorithm (Sanchez-Espigares & Lopez-Moreno, 2018). EM stands for Expectation Maximization and is used to find maximum-likelihood estimates for model parameters. The algorithm makes an initial guess of the parameters of the model and makes a probability distribution, and by trial and error it finds the parameters which maximize the probability of the observed data. The test will be performed for different orders of the AR process and with two regimes, as the benefits of adding a third regime in this M&A setting is unclear (Town, 1992). According to Town (1992) this Markov switching model should capture the wave structure in the data, if a wave structure is present.

The three models, simulation, straight line fit and Markov switching-regime model, will be tested on two industries, industrials and energy. The tests will be made on the data with monthly deal counts. Industrials is the industry with the most deals during the sample period and energy is the industry with the fewest number of M&A deals over the sample period.

6.2.3 Regressions, explanatory variables and M&A activity

6.2.3.1 Regressions / Applying the explanatory variables to the dependent variable

The related articles have different approaches to examining the explanatory variables and their explanatory power towards merger waves and aggregate merger activity. Mitchell et al. (1996) use a linear regression whereas Harford (2005) uses both a logistic and a linear model. The choice of the model depends on the dependent variable. Mitchell et al. (1996) use the M&A activity as the dependent variable whereas Harford (2005) uses a binary variable, merger wave state or non-merger wave state, as the dependent variable in the logistic regressions and M&A deal numbers as the dependent variable in the linear regressions. The difference between the linear regression and the logistic regression is that the linear regression gives a continuous output whereas the logistic regression provides a probability between 0 and 1.

A simple linear regression is given by the formula;

$$y = a + bx$$

y is the dependent variable, a is the intercept, b is a coefficient and x is the value of the explanatory variable. The parameters a and b are estimated using ordinary-least-squares (OLS). The OLS estimates are determined by finding the regression line, which gives the smallest sum of the squared deviations of the difference between the datapoints and the line (Navlani, 2018).

A logistic model is used to find the relationship between a dependent binary variable and a number of independent explanatory variables. The logistic model is given by the formula;

$$p = 1/(1 + e^{-(a+bx)})$$

a and b are the same parameters as in the linear regression, and p is the probability, which lies between 0 and 1. In this case the binary variable is given by a merger wave and a non-merger wave state. The logistic regression computes a probability, which is used to assign the observation point in question to one of the two states. If $p \geq 0.5$ then the observation is in a merger wave state and if $p < 0.5$ then it is in a non-merger wave state. The coefficients in the logistic regression is found through the maximum likelihood estimation (MLE) method. The MLE determines the parameters, which are most likely to produce the observed data (Navlani, 2018).

In this paper both the linear regression and the logistic model will be tested. For the logistic model the dependent variable can be measured in two different ways. The first approach is to only assign a 1 to the first month in each merger wave period, and then all other months is 0. The second approach is to assign a 1 to all the months which are in a merger wave state, and hence the months in a non-merger wave state is assigned a 0. Both measures will be tested on the data.

The performance of the models is evaluated through the log likelihoods, adjusted R-squared and the correlation of the predicted waves with the actual occurrence of waves. The logistic models are compared internally by comparing the log likelihoods. This is always a negative number and measures the probability of observing the given sample. The model with the best fit is the model with the smallest absolute value of the log likelihood (Baesens, 2014). Additionally, for the logistic regressions the correlation between the actual observed occurrence of a merger wave in a given period and the probability of a wave generated by the model can be calculated (Harford, 2005). Pearson's correlation coefficient between X and Y is calculated using (Agresti, Franklin, & Klingenberg, 2018):

$$\rho_{XY} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

The models with the highest correlations have the best fit and predictive power. The linear regressions are compared by looking at the adjusted R-squared. R-squared measures the proportion of the variance for the dependent variable that is explained by the explanatory variables. The adjusted R-squared is used as opposed to the R-squared, as the adjusted version has been modified by the number of explanatory variables in the model. The adjusted R-squared will only increase if a newly added explanatory variable improves the model more than would be expected by chance.

First all the explanatory variables are tested separately in univariate regressions, both logistic and linear regressions and for all eleven industries. Afterwards they will be tested in logistic and linear multivariate regressions with multiple combinations of the explanatory variables. There will be regressions only including neoclassical variables, regressions only including behavioral variables and also regressions including all the explanatory variables. The explanatory variables used in the regressions will be explained in the following sections. Each of the multivariate regressions will be reduced until they only contain variables, with a p-value of 0.05 or lower. This is done by removing the variable with the highest p-value, and then running the model with the remaining variables again. The variables are removed one by one until all the remaining variables has a significant explanatory power on the number of M&A deals or merger waves, depending on the regression type.

6.2.3.2 Explanatory variables

In this subchapter the measurement of the explanatory variables will be outlined. All the explanatory variables are calculated on a quarterly basis, at the industry-level and most of the variables are constructed as ratios to account for time differences. The explanatory variables are calculated based on end of period numbers. Therefore, the variables need to be lagged one period (t-1) to accommodate that the variables are forward-looking. Taking the sales growth in the neoclassical theory as an example. A big increase in the sales growth one quarter is expected to have an effect on the amount of M&A activity the subsequent quarter, therefore the variable effect must precede the M&A investment. Furthermore accounting-based variables such as the sales growth, asset turnover and Tobin's q may be affected by the M&A activity depending on the financing in the M&A deal and thereby generating a spurious correlation, which is yet another reason for lagging the variables (Andrade & Stafford, Investigating the economic role of mergers, 2004).

There will be two sets of explanatory variables, one to account for the neoclassical theories and one to account for the behavioral theories. The neoclassical variables are chosen to capture an economic shock to an industry's operating environment. These variables are sales growth, employment growth, cash flow margin on sales, Tobin's q ratio and MB ratio. The MB ratio is however a bit ambiguous, as it is also claimed by the behavioral hypothesis. The behavioral variables, which are chosen to reflect the overvaluation in the market, are the MB ratio, the standard deviation (sd) of the MB ratio, the one- and three-year stock returns and the sd of those returns. The calculations of the explanatory variables are displayed in table 1. The choice of the variables is motivated by papers by Andrade & Stafford (2004), Szücs (2016), Kastrinaki & Stoneman (2012), Harford (2005), Mitchell & Mulherin (1996) and more.

Variable	Definition
Tobin's q	$q = \frac{[book\ assets + market\ equity - book\ equity]}{book\ assets}$

Sales growth	$$g_{sales} = \left[\frac{sales(t)}{cpi(t)}\right] / \left[\frac{Sales(t-2)}{cpi(t-2)}\right] - 1$$
Sales shock	$$shock_{industry} = abs[sales\ growth(t) - mean(sales\ growth\ in\ all\ t)]$$ $$shock_{quarter} = abs[sales\ growth(industry\ i) - mean(sales\ growth\ in\ all\ industries)]$$
Employment growth	$$g_{employment} = \frac{Employmnet(t)}{Employment(t-2)} - 1$$
Employment shock	$$shock_{industry} = abs[employment\ growth(t) - mean(employment\ growth\ in\ all\ t)]$$ $$shock_{quarter} = abs[employment\ growth(industry\ i) - mean(employment\ growth\ in\ all\ industries)]$$
Cash flow margin	$$CF\ margin = \frac{EBITDA}{sales}$$
Market-to-book ratio	$$Market - to - book = \frac{Market\ capitalization}{Net\ book\ value}$$
Stock return	$$Stock\ return = \frac{P_1 - P_0 + D}{P_0}$$

Table 1: Explanatory variable calculation

6.2.3.3 Neoclassical explanatory variables

The neoclassical theory on merger waves rely on shocks, which are characterized as a factor that alters the industry structure. Mitchell et al. (1996) proposes to implement the sales and employee growth and shock variables as a proxy for industry performance. Both sales and employee growth are measured as the two-year change in values and are used as explanatory variables without further changes. This level measurement is meant to capture the marginal effect of the industry variables on the intensity of M&A activity across all industries (Harford, 2005).

The sales numbers are adjusted by the consumer price index to make the sales numbers for the two years comparable. A shock on the growth variables can be measured in different ways. The first method is measured in levels as the absolute change in for example sales growth in industry *i* at time *t* and the average sales growth for all industries at time *t*. An industry is said to experience a shock if it lies above the 67th percentile of the ranked absolute changes for the same time period. This quarter-adjusted variable is meant to capture the marginal effect of the industry specific variable for industries, where these variables are unusually high of low compared to the other industries in that quarter. The second shock method is measuring the absolute change in the sales growth of industry *i* at time *t* and mean sales growth for industry *i* across the whole sample period. In this case the absolute changes are ranked across time per industry, and the periods which are ranked above the 67th percentile are said to experience a shock. These industry-adjusted variables are meant to capture the marginal effect of the industry specific variables during periods where these are unusually high or low compared to the industry specific historical average (Andrade & Stafford, 2004). The absolute change is used in both measures as a shock can both be a big increase or a big decrease in the growth variable. These shock measures are made both for sales and employee growth. The sales and employee variables cover the years 2004 to 2018. They do not start before 2004 due to the calculation of the 2-year growth.

The cash flow margin is included as a measure of industry profitability. It captures some of the industry conditions but also includes elements of growth prospects. It is calculated at an industry level by taking the sum of EBITDA for companies within industry *i* and dividing with the sum of sales numbers for companies operating in industry *i* (Andrade & Stafford, 2004). The cash flow variable is also included as a dummy variable in order to try to measure a possible shock. The shock variables are measured both on a period and industry wise ranking as described with the sales and employment shock measures. The quarterly measured cash flow margin covers the period from Q1 2002 to Q4 2018.

Tobin’s q is included in the neoclassical explanatory variables as an estimate of growth opportunities. It is originally meant to describe firm-level investment, where high q firms buy low q firms (Jovanovic & Rousseau, 2002). However, as growth prospects are expected to be correlated across firms within the same industry, some industry-wide effects might be observable, which is why the variable is included here (Andrade & Stafford, 2004). Tobin’s q is both included as a continuous variable, but also as a dummy variable. Andrade and Stafford (2004) writes: “… assuming q-theory is well specified at the industry level, all forms of investment should be positively related to q.” As M&A is an investment form, M&A activity is expected to be positively correlated with q. The q dummy variables are calculated by sorting the industries by the q-ratio on a quarterly basis. There will be both a high q dummy variable, which will be equal to one if the industry's q is above the 67th percentile and a low q dummy variable, which will be one if the industry's q is below the 33rd percentile compared to all industry q's during the subsequent quarter. The q dummy variables are implemented as an attempt to identify industries with good or poor growth opportunities (Andrade & Stafford, 2004).

The MB ratio is included in the neoclassical explanatory variables as a proxy for growth opportunities (Harford, 2005). It is calculated as the market capitalization divided by the net book value witch is given by the formula; $Net\ book\ value = total\ assets - total\ liabilities$ (Berk & DeMarzo, 2017). This ratio is used to evaluate a company's market value relative to its book value, and thereby shows the market's perception of the value of the company. A ratio below 1 indicates that the market thinks the stock is worth less than the books states and a ratio above 1 indicates that the market think the stock is worth more than the books states. The MB ratio is a bit ambiguous, as the variables is also claimed by the behavioral hypothesis. The behavioral hypothesis uses it as a proxy for overvaluation in the market. This variable will be included in the multivariate regressions for both the neoclassical and the behavioral variables, but will also be excluded in both due to its ambiguity (Harford, 2005).

6.2.3.4 Behavioral explanatory variables

The behavioral models rely both on market valuations as well as on a high dispersion in these valuations (Shleifer & Vishny, 2003). The variables chosen to examine the behavioral hypothesis of market timing includes the MB ratio, the sd of the MB ratio, the average one-and three year stock returns and the intra-industry sd of those stock returns (Harford, 2005).

The calculation of the MB ratio has already been mentioned in the above section, and is included in the behavioral explanatory variables as a measure of market overvaluation. The sd of the MB ratio is calculated based on the calculated MB values and is measured on an industry level. The sd formula is given by;

$$\sigma = \sqrt{\frac{\sum(x - \bar{x})^2}{n}}$$

where x is the MB ratios within an industry, $\bar{x}$ is the mean MB ratio for the industry and n is the number of observations (Harford, 2005) (Cuthbertson & Nitzsche, 2004).

The stock returns are included in the behavioral explanatory variables as a measure of market valuation, and they are expected to be abnormally high before and possibly during a wave (Shleifer & Vishny, 2003). The one-and three-year stock returns are calculated using stock prices, which are adjusted for stock splits and dividend payments. A stock split or a dividend payment will most likely cause the stock price to decline post the event. If for example a dividend is paid, the stock price will in theory decline by the dividend amount. However, the stock price can decline more or less (even increase), but the difference will then be due to other company specific or market-wise factors. The adjusted stock price amends the pre-dividend stock price by only adjusting it for the non-dividend and non-stock split stock price movements. This makes the stock price comparable over time. The sd of the stock returns are calculated using the same formula as for the MB ratio (Cuthbertson & Nitzsche, 2004) (Shleifer & Vishny, 2003).

6.2.3.5 Explanatory variable combinations

For the neoclassical multiple linear regression models there will be four multiple regressions. The first one will include sales, employee, and EBITDA variables. The q variables are added in the second round, as they are originally a firm-specific factor. In the third round the sales, employee, EBITDA variables, and the MB ratio will be tested together. The MB ratio is not implemented in the model right away as it is also claimed by the behavioral hypothesis. Lastly all the proposed neoclassical variables are tested simultaneously. For the behavioral multiple linear regressions, two variable combinations are tested. In the first multivariate regression the stock returns, the sd of these returns, and the sd of the MB ratio variable are included. For the second behavioral regression the MB ratio is added to the other behavioral variables. Lastly all the variables, both the neoclassical and behavioral variables, will be implemented in the regression model at the same time.

6.2.3.6 Correlations

The correlations between the explanatory variables are calculated using Pearson's correlation formula presented in section 6.2.3.1. A correlation will be classified as a being strong if $\rho \geq 0.5$, it is said to be of moderate degree if $0.50 > \rho \geq 0.30$ and finally the correlation is said to be weak if $0.30 > \rho$ (Agresti, Franklin, & Klingenberg, 2018).

7. Results

7.1 Differences in the rate of M&A activity – Results

The first test applied to the industry deal data is the test of normality. The histograms, Q-Q-plots and the Sharpiro-Wilks test results can be found in appendix 5. The first thing to notice is that when the data is split into the 11 industries and the deal numbers are reported on a monthly basis, all of the Sharpiro-Wilks tests on the individual industries gives p-values below the commonly used 0.05 significance level and even below the 0.01 significance level. In addition to this looking at the histograms and Q-Q-plots, many of the industries have multiple local maxima on the histograms and a lot of the plots also have a positive skew. This means that the null hypothesis can be rejected, and hence the monthly M&A deal numbers are not normally distributed. When the deal counts are made on a quarterly basis for the 11 industries, three of the industries have a p-value above the 0.05 significance level while the remaining eight industries have a p-value below the 0.05 significance level. As a result, the null hypothesis, stating the data should be normally distributed, cannot be rejected for the industries financials, health care and utilities when the deal counts are made on a quarterly basis. For the remaining industries the test show that the quarterly deal counts are not normally distributed.

As a result of the lack of normality in almost all of the industry distributions, the Fligner-Killeen test is used to check for equality of variance across the industries. The test of the industry divided data with monthly deal counts gave a chi-squared = 842.38 with 10 degrees of freedom and a p-value below $2.2e^{-16}$. The same test on industry variation but with quarterly deal counts gave a chi-squared = 297.38, 10 degrees of freedom and a p-value also below $2.2e^{-16}$. The test results can be found in appendix 6. The low p-values mean that the null hypothesis stating that all the variances are equal across industries can be rejected, hence at least one variance is different from the others.

7.1.1 Equality of means

In testing for differences in the timing of the occurrence of M&A, the Welch's ANOVA and Kruskal-Wallis test were suggested. As previously mentioned, the Welch's ANOVA test assumes normality in the data, where the previous section showed, that this data is not normally distributed. But due to the size of the dataset and CLT, the Welsh ANOVA should still be applicable and provide correct results. The Welsh's ANOVA test on the industry specific data with monthly deal counts gave a F-statistic of 147.73 with 12 degrees of freedom and a p-value below $2.2e^{-16}$, see appendix 7. The p-value is below the significance level of 0.05, which means that the null hypothesis of equal means can be rejected and hence at least one group mean is not equal to the others. The Kruskal-Wallis test on the industry specific data gave a chi-squared = 1637.1 with 12 degrees of freedom and a p-value below $2.2e^{-16}$, see appendix 8. Also, in this test the p-value is below the significance level of 0.05 and hence the null hypothesis assuming that the groups are from identical distributions can be rejected.

7.2 Merger waves – Results

7.2.1 Merger wave identification method

As described in section 6.2.2 three methods were suggested to detect merger waves, namely simulations, removing straight line fit and Markov switching regime model. A summary of the number of waves identified from the different wave detection approaches and the different industries can be found in table 2. The graphs can be found in appendix 9.

Model	Industrials	Energy
Simulation	5	5
Straight line fit	33	53
Markov, AR(0)	2	1
Markov, AR(1)	44	16
Markov, AR(2)	36	15

Table 2: Number of identified M&A waves

As table 2 clearly shows, there is a big variation in the number of identified waves across the different approaches and also within the Markov switching regime model itself. A summary of the Markov model's coefficients can be found in appendix 9 below the graphs. It is not the same regime which is depicting the merger wave period in all the regressions, hence this needs to be determined first. The regime with the highest intercept is the regime, which is covering the merger wave period as the general level of M&A activity is expected to be higher during merger wave periods, and hence the regime with the lowest intercept covers the time periods with moderate M&A activity. This can be checked by looking at the graphs displaying regime 1, where the time intervals characterized by regime 1 are grey. The periods with the higher mean should be the wave periods. This is however rather difficult to see on the AR(1) and AR(2) models, as the regimes changes often.

Table 2 shows that the Markov model using an AR(0) process identifies the lowest number of waves followed by the simulation approach. For the industrials industry the Markov AR(0) model waves start earlier and last longer compared to the waves from the simulation method. At the same time the simulation method identifies three close waves at the end of the time series, where the Markov AR(0) model does not identify any change in regime. For the energy industry the Markov AR(0) model identifies one big wave that lasts around 130 months, which also includes the five waves identified through the simulation period. The model removing the best straight line fit and the two other Markov switching regime models with autoregressions of order one and two identify a lot more M&A waves than the two previously mentioned models.

7.2.2 Identified industry merger waves

Based on the above section the Markov switching regime model using AR(0) was chosen to identify the merger waves used in the rest of the thesis. The Markov AR(0) model was made both with monthly and quarterly deal counts, and for most industries it gave rather similar regime identifications. The models with monthly data gave the most significant results, hence this classification will be used in the remaining parts of the paper. The Markov switching regression results for both the monthly deal counts can be found in appendix 10. The number of merger waves within an industry and the average duration of the merger waves differ between the industries, see table 3 and appendix 11.

Industry	Number of deals	Number of waves	Average duration of merger wave, months	Average time between merger waves, months
Communication services	2,241	2	58	82
Consumer discretionary	5,817	2	34.5	41
Consumer staples	1,623	2	40	59
Energy	587	1	111	NA
Financials	4,225	3	27.67	13
Health care	1,417	22	2.45	8.57

Industrials	9,401	2	40.5	34
Information technology	928	3	36	45
Materials	2,908	2	40.5	43
Real estate	1,691	2	30	27
Utilities	1,547	15	11	4.71

Table 3: Industry merger waves

As table 3 shows, there is a big variation in the identified number of waves during the 22 years the time series covers. Most of the industries have two waves, and then there is health care and utility, which have 22 and 15 waves, respectively. These two industries are also the industries with the shortest average duration of a merger wave and shortest time between merger waves. The energy industry only experiences one wave, hence it is not possible to calculate the average time between merger waves.

The graphs in appendix 10 show that multiple of the industries experience waves at the same time. This is for example the case with consumer discretionary, consumer staples, financials, industrials, information technology, materials, and real estate which all experiences a big wave between August 2003 and October 2007. Additionally, all of the industries except for energy, health care, and utilities only experience wave activity in the period from January 1999 and until December 2007 with zero to two periods of normal merger activity.

7.3 Explanatory variables

In the following sections the results of the logistic and linear regressions will be presented. First the logistic univariate regression results will be presented followed by the linear univariate regression results. Afterwards the logistic and linear multivariate regression results will be presented and lastly the correlations between the explanatory variables will be scrutinized.

7.3.1 Univariate regressions

7.3.1.1 Logistic regressions

The first round of logistic regressions was made with the dependent variable being a binary variable with a 1 assigned to the quarter where a merger wave starts, and 0 otherwise. The regressions were made for all the sales and employee variables on all 11 industries. The results can be found in appendix 12. None of the sales and employee growth or shock variables had any significant explanatory power as to determine the start of a merger wave. Furthermore, most of the coefficient estimates are negative. This means that a one unit increase in for example sales growth in the energy industry will decrease the log odds of the start of a merger wave by 1.234.

The second round of logistic regressions was made on the dependent variable where the whole merger wave period is assigned a 1 and the non-merger wave periods are assigned a 0. The results can be found in appendix 13. The sign and size of the variable estimate and the level of significance varies across the different explanatory variables and across the industries. The two industries health care and utility, which were the industries with the most merger waves during the sample period, are the industries with the fewest significant explanatory variables. For the rest of the industries there are five to eight explanatory variables, which have a significant explanatory power on the dependent variable for that specific industry when tested in the logistic univariate regression. The significant explanatory variables vary across the industries, and all the variables have a significant explanatory power in at least one industry logistic regression. The variables with the most explanatory power across the different industries at the 0.05 significance level are the 3-year stock return sd, 3-year stock return, employee growth, sales growth, employee shock based on industry classification, sales shock based on industry classification and EBITDA margin. The variables are mentioned in order with the first variable being the one which is significant across the most industries. Both neoclassical and behavioral variables are represented on the list. The logistic regression results for the mentioned seven variables are displayed in table 4 below. The results will be presented in more detail below the table.

Industry	**3-year return Std dev**	**3-year stock return**	**Employee growth**	**Sales growth**	**Employee shock industry**	**Sales shock industry**	**EBITDA margin**
Communication services	0.004282 * (-56.64311)	0.004745 (-59.00498)	13.8885 *** (-29.94605)	19.352 *** (-27.55911)	0.4055 (-37.53266)	1.2040 * (-35.63687)	0.08881 (-43.66664)
Consumer discretionary	0.025392 *** (-43.10743)	0.020679 ** (-45.46258)	2.1951 (-35.36522)	-5.403922. (-31.45614)	-0.1823 (-35.38492)	-0.2877 (-35.31913)	-0.2226 (-37.20695)
Consumer staples	-0.005270 (-53.95082)	0.01091 (-53.1705)	0.7759 (-36.01191)	1.4555 (-35.97721)	2.5360 *** (-27.88439)	2.7191 *** (-26.92025)	-0.17556 * (-38.77358)

Energy	0.009436 * (-55.87464)	0.006693 * (-57.54338)	3.9597 * (-32.86133)	1.2736 (-37.23665)	-0.4124 (-38.1552)	-0.2877 (-38.28429)	-0.17197 ** (-36.82431)
Financials	0.005449 (-55.67252)	0.007199 (-54.26256)	9.167 ** (-11.21932)	0.3118 (-34.82567)	2.3224 *** (-28.39569)	-0.1823 (-35.38492)	0.01043 (-41.97279)
Health care	0.011519 * (-54.42765)	0.007547 (-55.02538)	5.101 (-37.44467)	-0.1253 (-38.00671)	0.6103 (-37.83521)	-0.6242 (-37.87082)	-0.10174 ** (-38.36849)
Industrials	0.018491 *** (-44.9288)	0.01845 *** (-45.25175)	15.4287 ** (-24.73165)	23.120 *** (-18.37966)	3.0164 *** (-25.11383)	1.3545 * (-33.65271)	0.05291 (-38.81126)
Information technology	0.008063 ** (-46.89047)	0.006654 ** (-48.51444)	9.7691 * (-30.52942)	-0.5146 (-32.95606)	-0.5754 (-34.08048)	-1.0415 (-33.27823)	0.02698 (-36.30739)
Materials	0.021149 *** (-40.19735)	0.022520 *** (-40.34706)	13.6660 ** (-23.20365)	9.9735 *** (-24.56685)	0.9491 (-33.25)	0.9491 (-33.25)	0.6713 ** (-30.34456)
Real estate	0.016495 ** (-44.44452)	0.007586 (-47.28945)	-0.02141 (-36.40151)	-5.3167 ** (-28.44971)	2.3238 *** (-29.69253)	2.2644 *** (-30.59627)	0.01184 (-41.25506)
Utility	0.004574 (-53.36278)	-0.011929 * (-50.27997)	-0.2088 (-33.44196)	-1.1967 (-33.22434)	0.4520 (-33.20838)	-0.7355 (-32.7387)	0.008086 (-36.81729)

*Table 4: Logistic univariate regression results for seven variables. The table displays the subsequent variable coefficient with the number in parenthesis being the log likelihood. *, **, *** indicates the significance codes at a significance level of 0.05, 0.01, and 0.001, respectively.*

7.3.1.1.1 Sales variables

The sales growth and industry-based sales shock variables are significant in four industry regressions each, where the period-based sales shock variable is only significant in one industry regression. The sign of the coefficients varies, with mot of the significant variables being positive. When looking at the log likelihoods, the logistic univariate regression with the sales growth variable is the one, which has the smallest absolute value of the log likelihood in most cases compared to the two other sales variables.

7.3.1.1.2 Employee variables

The results for the logistic regressions with the employee variables gave similar results to the sales variables. The employee growth and the industry specific employee growth shock are significant in the highest number of industry regressions, six and four respectively. The regressions with the employee growth variable are also the regressions with the smallest absolute value of the log likelihood in most industries. All the industries with a significant relation, has a positive relation between merger waves and the employee variable except for the real estate industry. When looking at all the coefficients, both significant and insignificant ones, the majority of them are positive.

7.3.1.1.3 EBITDA margin variables

For the EBITDA margin variables, the pure EBITDA margin variable is significant in four industries, the industry specific EBITDA shock is significant in three industries and the time-period specific EBITDA shock is significant in only one industry regression. The EBITDA margin and the industry shock variable are significant within the same three industries and with the same coefficient sign. The EBITDA margin coefficients are mainly positive as opposed to the two EBITDA dummies, which mainly has negative regression coefficients. The period-based EBITDA dummy is not applicable in three industries, simply because the variable is zero in all periods. For the log likelihoods the EBITDA margin and the industry-based EBITDA shock have the lowest log likelihood in five industries each.

7.3.1.1.4 Q variables

The q variable has a positive coefficient in ten of the eleven industries, where two of them are significant at a 0.05 level or above. The high q dummy variable has a positive coefficient in nine of the eleven industries, where two of them are significant. The low q dummy variable is mainly represented with negative coefficients, where three of them are significant. The low q dummy variable has the lowest absolute log likelihood in six industries, the q variable has the lowest in four industries and the high q dummy has the lowest absolute value in only one industry.

7.3.1.1.5 Market-to-book ratio variables

The MB ratio and MB sd are only significant in two and three of the industry regressions respectively. Both variables have a positive coefficient in most of the industry regressions. For the log likelihood the MB sd has the lowest absolute value of the log likelihood in six industries and the MB ratio has the lowest absolute values in the remaining five industries.

7.3.1.1.6 Stock return variables

Turning to the stock return variables, the one-year return and the sd of this return are only significant in one and three of the industry regressions, respectively. The sign of the relation with merger waves differs, with an overweight of positive relations for the one-year stock return where it is almost equally split between positive and negative coefficients for the one-year stock return sd. The three-year stock return variables are significant in most industry regressions across all the tested explanatory variables. The coefficient for both the three-year stock return and the sd of this return is positive in all cases except for the stock return for utility. When comparing the log likelihood of the logistic univariate models for the one- and three-year stock returns, the regression using the three-year stock return performs better (lower absolute log likelihood) in ten of eleven industry regressions. Comparing the two regressions using the sd of the two returns, the sd of the three-year stock return performs the best in seven industries. When comparing the two one-year stock return variables, the results are roughly equal as the one-year stock return has the lowest absolute value of the log likelihood in six industries and hence the one-year return sd has in five industries. For the three-year stock return variables, the sd has the lowest log likelihood in eight of the industries.

7.3.1.2 Linear regressions

In the linear regressions the dependent variable is the actual numbers of M&A deals, and hence not a binary variable as in the above logistic regressions. When the dependent variable is changed, so does the results. The eight explanatory variables which are significant in the most industry regressions are listed below in table 5. All the variables and their regression results can be found in appendix 14.

Industry	3-year return Sd	Low q dummy	q	3-year stock return	Market-to-book ratio	Sales growth	High q dummy	Sales shock industry
Communica-tion services	0.08467 *** (0.2031)	-7.923 ** (0.09928)	15.076 (0.04452)	0.04859 ** (0.1148)	-0.0004 (3.03e-06)	101.039 *** (0.4703)	1.334 (0.002877)	9.334 ** (0.1228)
Consumer discretionary	0.20011 *** (0.1242)	-20.654 *** (0.1787)	64.32 *** (0.2068)	0.13151 * (0.0636)	0.8157 * (0.05991)	-12.514 (0.0386)	19.524 *** (0.1673)	-6.835 (0.01838)
Consumer staples	-0.01086 (0.003733)	-4.368 * (0.08584)	29.620 *** (0.3309)	0.02181 (0.0107)	-0.04091 (0.0392)	16.380 ** (0.1133)	8.8765 *** (0.3624)	7.042 *** (0.2017)
Energy	0.010977 * (0.05993)	0.05455 (6.07e-05)	6.667 * (0.06784)	0.007283 (0.0266)	0.006961 (0.005006)	0.5628 (0.0031)	1.0188 (0.02164)	-1.8077 * (0.06641)
Financials	-0.17449 * (0.04947)	-9.030 ** (0.1085)	104.73. (0.05144)	0.001314 (2.35e-05)	16.537 *** (0.3324)	0.3905 (0.0008)	5.486 (0.04092)	4.350 (0.02293)
Health care	0.001477 (8.367e-05)	-5.2646 *** (0.1588)	7.486 ** (0.1457)	0.02025 (0.0256)	0.1379 (0.02025)	-0.3048 (0.0470)	3.1949 * (0.05847)	0.4013 (0.0009151)
Industrials	0.12282 (0.04247)	-28.842 ** (0.1377)	85.81 *** (0.2043)	0.24101 *** (0.167)	19.221 *** (0.1844)	203.063 *** (0.4531)	29.088 ** (0.1431)	28.697 ** (0.1329)
Information technology	0.020127 *** (0.1848)	-2.9495 ** (0.11)	3.165 (0.05024)	0.015818 *** (0.121)	1.2195 * (0.08387)	-0.3137 (0.0452)	0.7051 (0.006285)	-1.422 (0.02395)
Materials	0.07458 *** (0.1974)	-3.565 (0.02776)	17.151 (0.04205)	0.08007 *** (0.223)	7.127 * (0.09303)	29.886 *** (0.2066)	2.231 (0.01139)	1.318 (0.003621)
Real estate	0.08268 *** (0.1397)	-3.700 (0.04047)	48.32 ** (0.1078)	0.06392 ** (0.1156)	12.782 ** (0.1317)	-5.219 * (0.0848)	5.166 * (0.07887)	7.363 ** (0.1329)
Utility	0.07215 (0.0276)	-2.5798 (0.04299)	4.458 (0.01149)	-0.02860 (0.0382)	2.260 (0.04458)	-5.742 (0.0265)	1.0089 (0.006721)	-1.2410 (0.01017)

*Table 5: Linear univariate regression results for seven variables. The table displays the subsequent variable coefficient with the number in parenthesis being the adjusted R-squared. *, **, *** indicates the significance codes at a significance level of 0.05, 0.01, and 0.001, respectively.*

Comparing table 4 and 5 it shows that it is not the same variables that are significant in the two univariate regressions.

In general, the sales variables are significant in a higher number of linear regressions compared to the logistic regressions, but it is not a major difference. The sign of the coefficients is still split roughly equally between a positive and negative sign with the majority of the significant coefficients being positive.

The employee growth variable is significant in less industry regressions compared to the logistic regressions whereas only few changes have appeared for the shock variables. The majority of the coefficients is still positive for the employee growth and employee shock industry variables and the period employee shock is roughly equally split between positive and negative coefficients.

The EBITDA variables are significant in fewer industry regressions compared to the logistic regressions and the EBITDA period dummy is no longer significant in any of the industries. A couple of changes have appeared to the coefficient signs. These changes mean that the EBITDA margin is no longer pervaded by positive coefficients, but a more equal split, and the opposite is the case for the industry EBITDA dummy, which is now equally split between positive and negative coefficients compared to the logistic overweight of negative coefficients.

The variables with the biggest difference from the logistic regressions are the q variables, which are now significant in three to four more industry regressions per variable compared to earlier. The coefficients have not changed much from the logistic regressions, but now all the q and high q dummy coefficients are positive and only one low q dummy coefficient is positive.

The MB ratio is now significant in six of the eleven industries compared to the previous two and the MB sd is now only significant in two industries instead of three. For both variables some of the previous negative coefficients are positive in the linear univariate regression, and hence both variables mainly have positive coefficients.

The results of the one-year stock return variables have changed slightly with one and two more significant industry regressions and the coefficients of the one-year stock return sd is now mainly positive. For the two three-year stock return variables there is one less significant case with each variable compared to the logistic regressions. The sign of the coefficients has not change except from one case in the sd variable.

It should be mentioned that most of the significant relations between one of the explanatory variables and the merger wave or non-merger wave state are still significant when the regressions are linear and with the M&A deal numbers as the dependent variable. The sign of the different linear regressions has in general not changed much from the logistic regressions.

7.3.2 Multivariate regressions

The multivariate regressions are made just as the univariate regressions, first as a logistic regression with the merger waves as the dependent variable and afterwards as a linear model with the M&A numbers as the dependent variable. At first the multivariate models using the neoclassical variables will be presented followed by the multivariate models with the behavioral models and finally the multivariate model including all the discussed explanatory variables. Only the reduced models containing 0.05 level significant variables will be discussed below. The logistic multivariate regression results can be found in appendix 15 and the linear multivariate regression results can be found in appendix 16. The correlation of prediction with waves for the logistic multivariate regressions and the adjusted R-squared for the linear multivariate regressions are presented in table 6. Table 7 displays the significant explanatory variables in the full neoclassical, full behavioral, and all variables logistic multivariate regressions.

	Logistic multivariate regression				**Linear multivariate regression**		
Industry	**Full neoclassical model**	**Full behavioral model**	**All variables**		**Full neoclassical model**	**Full behavioral model**	**All variables**
1 Communication services	0.7731	0.6920	0.7731		0.7767	0.2714	0.7767
2 Consumer discretionary	0.8746	0.1464	0.8746		0.4818	0.3279	0.4775
3 Consumer staples	0.5379	-	0.7164		0.5438	0.1154	0.5954
4 Energy	0.6698	0.7777	0.8513		0.2445	0.0556	0.2445
5 Financials	0.7904	0.8746	0.8746		0.4338	0.5039	0.5276
6 Health care	0.5523	0.2303	0.2155		0.2662	0.1492	0.2430
7 Industrials	0.7976	0.7602	0.8789		0.7258	0.6348	0.7602
8 Information technology	0.8285	0.3620	0.5559		0.2395	0.0959	0.3031
9 Materials	0.8248	0.6455	0.8746		0.3258	0.3816	0.3468
10 Real estate	0.6838	0.3727	0.6838		0.3822	0.1776	0.3822
11 Utility	-	-	-		-	0.0565	0.0565

Table 6: For the logistic multivariate regressions the correlation of prediction with the identified merger waves is presented. For the linear multivariate regressions the adjusted R-squared is presented.

7.3.2.1 Logistic multivariate regressions

LOGISTIC MULTIVARIATE REGRESSIONS

	Sales growth		Sales shock quarter		Sales shock industry		Employee growth		Employee shock quarter		Employee shock industry		EBITDA margin		EBITDA shock quarter		EBITDA shock industry	
	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	A
1. Communication services							X	X					X	X				
2. Consumer discretionary	X	X															X	X
3. Consumer staples						X						X						
4. Energy							X		X	X	X	X	X	X				
5. Financials																		
6. Health care												X					X	X
7. Industrials		X					X				X							
8. Information technology					X	X	X	X									X	
9. Materials	X						X	X										
10. Real estate							X	X			X	X						
11. Utility																		

	q		high q dummy		log q dummy		Market-to-book ratio			Market-to-book sd		1-year stock return		1-year stock return sd		3-year stock return		3-year stock return sd	
	N	A	N	A	N	A	N	B	A	B	A	B	A	B	A	B	A	B	A
1. Communication services							X	X	X	X								X	
2. Consumer discretionary			X	X	X	X												X	
3. Consumer staples																	X		
4. Energy	X		X							X				X	X		X		
5. Financials							X	X	X			X	X						
6. Health care		X			X											X			
7. Industrials	X						X			X				X	X			X	
8. Information technology	X				X									X	X				X
9. Materials							X								X		X	X	
10. Real estate	X	X																X	
11. Utility																			

Table 7: Reduced logistic multivariate regression results. The X indicates that the specific variable is significant at a 0.05 level for the N, B, and A variable combinations. N = full neoclassical model, B = full behavioral model, A = all variables.

7.3.2.1.1 Sales, employee, EBITDA margin

The consumer discretionary and utility reduced logistic multivariate regressions do not include any of the sales, employee or EBITDA variables. In two of the reduced industry regressions only one variable is significant, this is employee period shock in the financials industry and industry EBITDA dummy in health care. These industries are the ones with the lowest correlation of prediction with waves, -0.0835 and -0.0976 respectively. In five of the reduced models two variables are significant. In three regressions it is a combination of a sales and an employee variable and in two cases it is an employee and EBITDA variable. The employee growth is the variable, which is present in the most industry regressions, followed by the period employee shock and industry EBITDA dummy. The remaining variables are present in two industry regressions each except from period sales shock and period EBITDA dummy, which are not present in any of the reduced regressions. In the majority of the significant cases the variable were also significant in the logistic univariate regression.

7.3.2.1.2 Sales, employee, EBITDA margin, q

The added q variables are significant in five, three and three industries for the q ratio, high q dummy, and low q dummy, respectively, split over seven industries. In most of the significant cases the q variables were not significant in the logistic univariate regressions. In four of these industry regressions one or two of the q variables have been added to the significant variables from the first multivariate logistic round with no change in the other variables. The consumer discretionary industry regression now includes the two q dummy variables, industry EBITDA margin and the sales growth, whereas none of the variables gave significant results when the q variables were not included. On the contrary the consumer staples reduced regression no longer includes any significant variables. For the remaining three industries some of the significant variables have changed. In eight industries have the performance improved after adding the q variables compared to the previous regressions.

7.3.2.1.3 Sales, employee, EBITDA margin, market-to-book ratio

The addition of the MB ratio has caused changes in three reduced industry regressions compared to the first multivariate regression round. In the communication services industry, the MB ratio has just been added to the previous significant variables. In the financials industry, the period employee shock has been removed and only the MB ratio is left in the reduced model. In the health care industry, the MB ratio, EBITDA margin and industry employee shock are included in the reduced model where only the industry EBITDA dummy were included previously. In the first two industries, the correlation with the actual wave occurrence has increased compared to both of the previous multiple regressions. For the health care industry, it has increased compared to the first multivariate regression, but not the second.

7.3.2.1.4 Sales, employee, EBITDA margin, q, market-to-book ratio

In two industries are the results as in round three with the MB ratio, in five industries the results are the same as in the second round of logistic multivariate regressions with the q variables, in two industries there are no variables included, hence the remaining two industry regressions are the only ones experiencing a change. In the industrials industry both the q ratio and the MB ratio are included in the reduced model. In addition to this the employee growth is now included instead of the sales growth variable. In the materials industry the two previous EBITDA and employee shocks are no longer significant, and instead have the sales growth been added along with the MB ratio. In the two industries where there are changes compared to the previous multivariate regressions, the log likelihoods have decreased and the correlation with the actual wave occurrence have increased.

7.3.2.1.5 Stock returns, stock return sd, market-to-book sd

For the consumer staples and utility industries none of the behavioral explanatory variables are significant in the reduced multivariate regressions. The three-year stock return sd is included in four industry regressions, and it is the only significant variable in three of these industry regressions. The health care and information technology industries do only include one behavioral variable each, the three-year stock return and one-year stock return sd respectively. The remaining industry regressions include two or three variables with three of them including both the one-year stock return sd and MB sd. The only two industry regressions which generate a higher correlation of prediction with waves compared to the neoclassical regressions are energy and financials, which both include the one-year stock return sd and MB sd variables.

7.3.2.1.6 Stock returns, stock return sd, market-to-book sd, market-to-book ratio

The addition of the MB ratio has resulted in changes in three industry regressions compared to the previous multivariate regressions. The first is communication services where the two MB variables are added to the previous significant three-year stock return sd. Here the correlation of prediction with waves have increased from the previous regression. The second case is financials where the MB ratio is significant along with the one-year stock return. The correlation is the same as before, but the absolute value of the log likelihood has decreased. The third case is materials, where the three-year stock return sd is now significant and the previous 1Y stock return sd and 3Y stock return is no longer. Here the correlation is also the same as in the previous multivariate regression, and the log likelihood has increased.

7.3.2.1.7 All explanatory variables

Five of the industries have reduced multivariate models where both neoclassical and behavioral variables are included with between two and five variables in total split between nine different variables. The combinations between the behavioral and neoclassical variables differ from industry to industry. One thing to notice is that none of the q or MB variables are included in these five industry regressions. In four of these industries the correlation of prediction with waves is the highest across all multivariate regression combinations. For the remaining five industries, one only includes behavioral variables and the other four only includes neoclassical variables.

7.3.2.2 Linear multivariate regressions

Table 8 displays the significant explanatory variables in the full neoclassical, full behavioral, and all variables linear multivariate regressions.

	Sales growth		Sales shock quarter		Sales shock industry		Employee growth		Employee shock quarter		Employee shock industry		EBITDA margin		EBITDA shock quarter		EBITDA shock industry		q		high q dummy		log q dummy		Market-to-book ratio			Market-to-book sd		1-year stock return		1-year stock return sd		3-year stock return		3-year stock return sd	
LINEAR MULTIVARIATE REGRESSIONS																																					
	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	B	A	B	A	B	A	B	A	B	A	B	A
1. Communication services	X	X					X	X			X	X	X	X					X	X					X	X	X									X	
2. Consumer discretionary	X	X	X														X	X			X	X	X	X				X		X		X			X	X	
3. Consumer staples	X	X																			X	X			X				X		X			X		X	
4. Energy											X	X	X	X					X	X						X		X									
5. Financials																				X					X		X	X				X	X	X	X	X	X
6. Health care											X	X								X			X											X			
7. Industrials	X	X					X	X			X	x		X					X							X	X	X	X	X		X	X	X			
8. Information technology									X	X	X	X							X					X				X	X								
9. Materials									X																X	X									X	X	
10. Real estate							X	X			X	X														X		X									
11. Utility																																X	X				

Table 8: Reduced linear multivariate regression results. The X indicates that the specific variable is significant at a 0.05 level for the N, B, and A variable combinations. N = full neoclassical model, B = full behavioral model, A = all variables.

7.3.2.2.1 Sales, employee, EBITDA margin

Most of the industry specific multivariate regressions includes two or three of the explanatory variables with sales growth, employee growth and the industry specific employee shock as the most common variables. Only four of the ten industries with significant reduced regressions includes both a sales and an employee variable. For the industries consumer discretionary, health care, and information technology, none of the sales, employee, or EBITDA variables were significant when they were applied in the univariate regressions. However, combining these variables have led to some reduced regressions with a couple of the variables being significant. The EBITDA variables are poorly represented with only three significant cases. In most of the reduced regressions the coefficients of the variables are positive just as in the univariate regressions.

7.3.2.2.2 Sales, employee, EBITDA margin, q

The second round of the multivariate regressions adds the three q variables to the explanatory variables list. For five of the ten industries with significant variables, the q variable is included. The q dummy variables are present in one industry regression each. All three q variables are represented in fewer industry regressions compared to the linear univariate regressions. The significant employee variables have not changed much from the previous multivariate regression, neither in number of significant cases or which industries they are significant within. The EBITDA variables have changed a bit from the previous multivariate regressions. The biggest change is for the sales variables. It is especially apparent for the industry specific sales shock, which is no longer included in any of the industry regressions. The industry regressions previously including this sales shock variable now includes the q variable. The other two sales variables have been reduced by one significant case, and no further change in the industries. Most of the variables seem to keep the sign of the coefficient from the univariate regressions. For eight of the industries the addition of the q variables has increased the adjusted R-squared of the model to a smaller or bigger extent depending on the industry.

7.3.2.2.3 Sales, employee, EBITDA margin, market-to-book ratio

In the third round of the multivariate regressions the sales, employee, EBITDA variables, and the MB ratio is included as the explanatory variables. The first thing to notice is that out of the six industries with a significant result for the MB ratio in the linear univariate regressions, the MB variable is included in five of the reduced linear multivariate regressions. When comparing the significant variables in the reduced regression results with the variables from the first round, they are quite similar in number and industries just with the MB ratio added. The biggest change is the employee growth which is no longer significant in the financials and materials industries. The EBITDA margin is now only represented in the communication services industry and none of the EBITDA shocks are significant in any of the industry regressions. Again, the sign of the explanatory variable coefficients seems to be consistent with the univariate regressions. When it comes to the performance of the reduced models, the addition of the MB ratio results in an increase in the adjusted R-squared value compared to the first round. For all industries, except two, the adjusted R-squared is lower in this round compared to when the q variables were included.

7.3.2.2.4 Sales, employee, EBITDA margin, q, market-to-book ratio

In the fourth round all the neoclassical variables are included. For the sales, employee, and EBITDA variables, the results seem to be pretty much the same as for the sales, employee, EBITDA, and q arrangement. For the q variables all the same variables as in round two are significant with the only exception being the consumer discretionary industry, where the q variable is no longer included in the reduced model, but now both the low and high q dummy variables are. As for the MB ratio, it is now appearing in four (previously five) of the ten industry reduced industry regressions. Two of the industries are the same as in the previous round of explanatory variable testing, and in none of these industries are any of the q variables significant. The two other MB significant industries include one q variable in the reduced model. In only four of the industries has the adjusted R-squared increased from round two. The biggest change in the adjusted R-squared is in consumer staples (includes both high q dummy and MB ratio), where it has increased approximately 0.05 from round two.

7.3.2.2.5 Stock returns, stock return sd, market-to-book sd

For the behavioral hypothesis the first test includes the one- and three-year stock returns as well as the sd of these along with the MB ratio sd. When comparing the five explanatory variables, the one-year return is the variable with the lowest explanatory power, as it is only significant in one regression, namely the consumer discretionary industry regression. This variable was significant in three other industries in the linear univariate regressions. The sd of the one-year stock return and the MB ratio sd both have significant explanatory power in four of the eleven industries. For the three-year stock return it is still significant in six of the eleven industries. However, in three of the six instances the three-year return were not significant within that industry for either the logistic or the linear univariate regressions. In two of these cases the three-year stock return is supplemented by the sd of this return. The sd of the three-year stock return is included in five of the industry specific reduced multivariate regressions, which is fewer than for both types of the univariate regressions. In six of the eleven reduced industry regressions only one variable is left in the reduced model. In three cases it is the three-year stock return, in two cases the sd of the three-year stock return and the last case is the sd of the one-year stock return. For the five remaining reduced regressions the combination of the included variables varies. Most of the variables seem to have a positive coefficient in the multivariate regressions, with the exception being the sd of the one- and three-year stock returns, which are both negative in two of the reduced models they are included in. When comparing this model to the full neoclassical model, the adjusted R-squared has increased in three industries, where one of them is utility, in which none of the neoclassical variables were included in the multivariate models.

7.3.2.2.6 Stock returns, stock return sd, market-to-book sd, market-to-book ratio

The second round of multivariate regressions for the behavioral explanatory variables included the variables as just discussed above as well as the MB ratio. For six of the industry specific regressions the results are the same as when the MB ratio was not included. For the remaining five industries some changes or additions have occurred. For the energy, materials and real estate industries each industry had either the three-year stock return or the sd of this return included in the previous round of multivariate regressions. In this round these variables are no longer included in the reduced multivariate model, but the MB ratio is. For the materials industry the three-year return is no longer included in the reduced multivariate model, but the sd of the three-year return is. The significance of the 1-year stock return variables does not change notably. In three of the five industries the MB ratio and the sd of this ratio both occurs in the reduced model. In only three of the industries has the adjusted R-squared increased after the addition of the MB ratio.

7.3.2.2.7 All explanatory variables

Of the eleven industries four of the multivariate industry regressions only include neoclassical variables, two only include behavioral variables and the remaining five industry regressions include both neoclassical and behavioral variables. For the consumer discretionary industry, the three-year stock return is added to the full neoclassical model but without the period sales shock. For the consumer staples industry two behavioral variables, the MB ratio sd and the one-year stock return, are added to the previous significant neoclassical variables excluding the previous significant MB ratio. For the financial industry the complete model is quite similar to the two behavioral multivariate models except that the MB ratio is included instead of the MB ratio sd and also the q variable is included. For the industrials full reduced regression, the q variable is excluded, the EBITDA margin is newly included along with the two MB variables and the sd of the one-year stock return. Finally, for the information technology industry the low q dummy is added to the significant variables from the last neoclassical multivariate regression, and the q variable is no longer significant. Additionally, the MB ratio sd is the only significant behavioral variable, which was also the case in the multivariate behavioral models. For five of the industries the full model has a higher adjusted R-squared than any of the previous models.

7.3.3 Correlations

The average correlations between the different explanatory variables is displayed in a correlation matrix in appendix 17. In general the sign and strength of the correlations differ, with most of the correlations being weak.

In general, the correlations between the explanatory variables within the same variable group, i.e. the three sales variables for example, are positive, and many of them are strongly correlated with correlations above 0.5. Weakly positive correlations are especially found in the employee and sales groups, where multiple of the industry specific correlations are negative in these two groups. The only exception from the positive correlations is the correlations between the low q dummy variable and the other two q variables, which is strongly correlated and negative in all the industry specific correlations. Most of the average correlations between the different neoclassical variables are weakly positive. The variable that stand out the most from this is the low q dummy variable, which on average is negatively correlated to all other neoclassical variables except for the two sales shock variables. In addition to this the EBITDA variables are on average negatively correlated with multiple of the sales and employee variables.

The correlations between the behavioral models are on average positive except for the sd of the one-year stock return, which is weakly negative for the MB variables and the three-year stock return variable. When it comes to the correlations between the neoclassical and behavioral variables, they are mainly positive between 0.01 and 0.2. The MB ratio sd has a weak negative correlation with eight of the neoclassical variables and also here the sd of the one-year return has a negative correlation with approximately half of the neoclassical variables.

8. Discussion

8.1 Equality of variance and means

In the Fligner-Killeen test, where the equality of variance was tested between the eleven industries, the null hypothesis was rejected. The rejection of the null hypothesis states that one or more industries experience a greater variation in the number of M&A deals compared to the other industries. This shows that there is an actual difference between the industries. In the Welch's ANOVA test the null hypothesis was rejected, hence the industry means are not equal. However, which mean and if there are multiple means which are not equal to the rest cannot be concluded based on the applied tests. The null hypothesis in the Kruskal-Wallis test was also rejected showing that the industry specific datasets were not from identical distributions. The fact that all three hypotheses are rejected indicates a significant variation in the time-series pattern of M&A across industries. This supports the division of the data into industries and indicates that the level and timing of industry specific merger activity could be at least partly explained by industry specific factors.

8.2 Merger wave identification method

The straight line fit model and the Markov switching regime models with autoregressions of order one and two seem to be much more affected by the volatility of the monthly number of M&A deals compared to the simulation method and Markov switching AR(0) model. One of the implications arising when using the straight-line fit model is that linear models are not able to capture nonlinear patterns such as asymmetry and volatility clustering (Olive, 2017). The M&A deal data fluctuates a lot in most of the eleven industries with a lot of smaller or bigger spikes and there is no consistent increase or decrease in the deal number, see figure 2. A large volatility in the data will cause the slope of the moving 5-year line to change a lot through time with changing positive and negative slopes. This has caused the straight-line fit model to identify a lot of waves due to the model's hypersensitivity towards constant changes in the M&A activity of both increasing and decreasing nature. The hypersensitivity towards outliers makes this model subject to identification error when it comes to merger wave identification.

As the Markov switching models with AR(1) and AR(2) takes the one and two previous deal counts, respectively, into account in the determination of the current state, they are obviously also more affected by the fluctuation in the monthly deal counts as opposed to the Markov model using AR(0) process, as it does not take any previous values into account. Again, the fact that there is a high fluctuation in the monthly number of M&A deals has caused the Markov AR(1) and AR(2) models to identify at least three times as many waves as the simulation and Markov AR(0) models. Additionally, both test industries are classified as being in a merger wave state in most of the months throughout the whole data period, which seems unsustainable. When comparing the three Markov switching regime models, the AR(0) model seems to be the one fitting the data the best, when compared to the aggregate merger waves presented in chapter 3.2 and the facts mentioned above. Additionally, for the AR(0) model, all the coefficients are significant on at least a 0.05 level, whereas the AR(1) and AR(2) models have at least one coefficient, which is not significant.

Harford (2005) argues that the aggregate merger waves are a byproduct of the industry specific merger waves, which tend to cluster over time due to a liquidity constraint. If this is assumed to be true, then the one to five merger waves identified with the simulation and Markov AR(0) methods are much more in line with the six acknowledged aggregate merger waves described earlier than the other three methods and their +15 waves. The discussion of which quantitative model is the best in explaining the M&A activity across Europe lies therefore between the Markov switching model using an AR(0) process and the simulation method. The simulation model is based on multiple subject choices in determining the merger wave period and also the split of the data period as described in section 6.2.2. The simulation was based on a two-year wave period chosen based on research made by Mitchell and Mulherin (1996). However, the choice of two years seems to be chosen rather arbitrarily, also compared to the acknowledged aggregate merger waves, which on average last 7.5 years. The data was divided into two sub-datasets to account for the aggregate changes over time. Where the data was split, was also a rather subjective decision. As a consequence of these subjective choices made in the simulation approach, the Markov switching AR(0) model seems to be the most objective and reliable approach to explain the M&A activity in Europe and thereby determining the merger wave periods.

8.2.1 Identified industry merger waves

Most of the industries have been identified to experience two waves during the latest 22 years, which seems reasonable thinking of the previously mentioned recognized aggregate merger waves. Compared to this, the 15 and 22 waves identified for the utilities and health care industries respectively, seem to be quite a lot of waves. When looking into the graphs and tables for the two industries in appendix 10 and 11, health care has a lot of small wave periods (regime 2) where most of them are not lasting more than two months, and the model seem to consequently recognize a monthly deal number above 10 deals as a wave period. Additionally, the waves seem to be occurring often throughout the data period, which the average time between merger waves also shows. For utilities the merger waves are longer, 11 months on average, compared to the health care industry, but still not as long as the remaining industries' merger waves. Due to the longer merger waves and the frequency, the utility industry is experiencing a merger wave more than 50 percent of the time. Another industry which stands out is the energy sector, where only one wave is identified with a duration of 111 months, which is almost twice as long as the second longest average wave period.

How precise the Markov AR(0) model is in identifying merger waves for the different industries is difficult to determine. When looking at the eight industries, communication services, consumer discretionary, consumer staples, financials, industrials, information technology, materials, and real estate, the average length of a merger wave is 38 months or three years and two months. This does not seem unrealistic when compared to the duration of the aggregate merger waves. Additionally, the eight industries all experience a merger wave during the last acknowledged aggregate merger wave from 2004 to 2008, and none of them are classified as experiencing a merger wave during the financial crisis in the end of 2008 and all of 2009. This clustering of industry waves is consistent with Harford's (2005) finding that industry specific merger waves tend to cluster and form aggregate merger waves. The Markov model has however some limitations. The model is dividing the data into two regimes, and in some cases the regimes are merger wave or normal merger activity regimes whereas in other cases the regimes might be high level of normal M&A activity or low level of normal M&A activity. The model is not able to differentiate between these two, as there is no benchmark for when a regime is a wave or when it is just a high level of normal M&A activity. Therefore, the model has identified at least one wave period in each industry, even though some industries might not have experienced any wave activity. It could for example be discussed whether the three industries energy, utility, and health care do experience merger waves whatsoever due to a couple of issues. First of all, they are all some of the industries with the lowest number of deals throughout the data period. This can have implications for the reliability of the tests as stated previously. Another fact that suggest the Markov AR(0) model could be wrong in the identification of waves in these industries is that both the utility and energy industries are classified as experiencing a merger wave during the financial crisis in the end of 2008 and 2009. This seems unusual considering the circumstances of the financial markets at that point in time (Swagel, 2013). Additionally, these three industries all provide some kind of necessity and can be classified as being in another economic environment possibly with a different M&A culture compared to the remaining industries.

8.3 Explanatory variables and regressions

The univariate regressions were implemented in the analysis as an attempt to identify whether the impact of neoclassical shocks and behavioral misvaluation were possible to measure and whether they have any explanatory power towards M&A activity and merger waves when tested on their own. Below it will be discussed whether the sign of the variable coefficients is in accordance with the two theories and the performance of some of the variables will be compared and linked with the correlations between the explanatory variables.

8.3.1 Logistic univariate regressions

8.3.1.1 Merger wave start

The first logistic regressions were made with the start of a merger wave as the dependent variable. The fact that none of the sales or employee variables gave any significant results in these logistic regressions does not mean that the industries did not experience an abnormal increase or decrease in one or more of the tested variables just before the start of a merger wave. It shows from the calculation of the shock variables that some of the industries are experiencing multiple large increases or decreases in some of the variables. However, based on the results in appendix 12 the applied variables do not seem to have any significant explanatory power in explaining the start of a merger wave. Eight of the eleven industries only experienced one merger wave during the time period from 2004 to 2018, and hence the dependent variable is zero in 59 quarters and one in only one quarter in these eight industries. As a result of the limited number of merger waves in the dataset it is difficult to find a significant relationship between the start of a merger wave and any explanatory variable. This might explain some of the insignificance, but it can also be that the variables just do not have any explanatory power. Which one is the correct conclusion is difficult to know, and further tests should be made to be able to answer this question.

8.3.1.2 Sales variables

The positive and significant sales growth variables indicate that merger waves are related to high-growth industries due to the positive relation, which is in accordance with the neoclassical theory. At the same time the fact that the sales growth shock sorted by industry has a positive relation to merger waves indicate that merger waves are related to industry change, rather than only to high- or low-growth industries, as the shock covers both big sales growth and big sales declines. This is somewhat contradicting. The sales growth and the sales industry shock are significant in the same three industries out of four significant cases for each variable. This could indicate that the two variables are capturing some of the same industry changes, and that the shock variable mainly consists of big increases in the sales growth rather than big decreases, and as a result of this that merger waves are related to high sales growth industries. If this is the case, we would expect the two variables to have a strong and positive correlation. This is however not the case with an average correlation of 0.16 between the two variables (Lund Research Ltd, 2018). This indicates that the sales growth and the industry sales shock variables partly capture different industry movements, hence the shock variable also includes big sales decreases. Parts of the low correlation can however also be explained by the fact that the correlation is calculated between a binary and a continuous variable.

The fact that the industry sorted sales shock is significant in more industries than the time-period sorted sales shock variables indicate that the shock should be measured relative to the development in the industry over time rather than being compared to the whole market in a specific period. These results connect to the fact that multiple of the industries experience merger waves at the same time as previously mentioned.

When the period-based shock variable was measured, only the four industries experiencing the highest abnormal change in that quarter were classified as experiencing a shock. It was not taken into account whether some industries had big fluctuations in the sales growth over time. As a result, some of the industries were classified as experiencing a shock in most of the quarters whereas other industries did not experience a shock when it was measured this way. Additionally, some industries were classified as experiencing a shock in periods even though they might not have experienced one if we look at the changes over time for that industry. This might be happening just because the other industries experienced even lower changes. At the same time the industry-based shock variable can give wrong results as well. Again, in the identification of the industry sales shocks the 67^{th} percentile was used, and hence all industries were classified as experiencing 20 shocks. It could be that an industry was experiencing more or fewer shocks. The method of identifying the shock variables are identical to the method used by Harford (2005) and Mitchell et al. (1996). It seems like this shock identification method is identifying big differences or shocks in the variables, but it might also be subject to error. However, it is out of the scope of this study to examine how big this error might be.

The sales growth and the industry sales shock had significant explanatory power in four industries each, but the regressions with the sales growth variable had the lowest absolute value of the log likelihood in the majority of the industry regressions compared to the two sales shock variables. The sales growth variable is thereby the best performing variable in most industries compared to the two other sales variables, when it comes to explaining merger waves. Part of this might however be due to the measuring of the shock variables as discussed above.

8.3.1.3 Employee variables

The fact that the industry wise employee shock variable is significant when it comes to explaining industry merger waves indicates that the occurrence of merger waves is related to big changes in the employee numbers rather than just being related to high employee growth industries. At the same time the employee growth variable in itself is also significant indicating that merger waves are related to high employee growth industries. This gives the same contradicting results as with the sales variables. In contrast to the sales variables, the two employee variables are not significant in all the same industries, hence it seems like the two variables capture different industry changes. The average correlation between the employee growth and the industry employee shock variables is 0.2794 (see appendix 17). Again, as the correlations are low, the shock variable seem to be capturing sales decreases as well. In the two industries, financials and industrials, the correlation between the variables is 0.61 and 0.50, which seems to be strong. The high correlation in financials and industrials indicates that the shock variable in the two mentioned industries mainly consist of big increases in employee growth, whereas a smaller correlation indicates that the shock variables are also capturing some big employee growth decreases. For the employee shock variables, the previous discussion about the classification of a shock for the sales variables is also relevant in this case. The mentioned results indicate that the shock variables are capable of detecting some of the big industry changes as intended, and the positive coefficients are in accordance with the neoclassical theory predicting a positive correlation between shocks and M&A activity.

8.3.1.4 EBITDA margin variables

For the three EBITDA margin variables the sign of the coefficients differs from industry to industry, which makes it hard to draw any conclusions for these variables. What can be said is that the merger waves do not seem to be driven particularly much by high EBITDA margins, as the dummy variables identifying these high EBITDA margin periods, most often have a negative coefficient, indicating merger waves are negatively related to EBITDA margin shocks. However, the EBITDA margin variable has a positive coefficient in seven industries and hence indicate that merger waves are related to high EBITDA margin industries. These results are contradicting, hence it is questionable whether the EBITDA variables have any consistent explanatory power when it comes to merger waves. The fact that the EBITDA margin dummy variables are a translation of the EBITDA margin into dummy variables yields an expectation of a high correlation between the EBITDA margin and two dummy variables. The results are in accordance with this prediction as the lowest correlation between the EBITDA margin and industry-based EBITDA dummy variable are 0.3961 and with an average of 0.66. The discussion mentioned under the sales variables regarding the identification of a shock is also applicable for the BEITDA shocks.

In general, for the three variable groups sales, employees and EBITDA margin, the industry specific shock variable explains the merger waves better than the time-period shock variable. This indicates that the industry specific development over time has a better explanatory effect on the occurrence of merger waves, compared to the period specific comparison. This is in alignment with the identified merger waves, where there are periods, where none of the industries experiences a merger wave.

8.3.1.5 Q variables

The q-theory predicts a positive relation between high q firms and M&A activity, the results in all the logistic regressions using the q variable are in accordance with these expectations. The high and low q dummy results indicate that merger waves are related to high q industries and not low q industries, just as predicted. The correlation between the q and the high q dummy variable is strongly positive at 0.81, which was expected, due to the identification of this dummy (see section 6.2.3.3). The correlation between the q variable and the low q dummy is strongly negative, -0.74, as this dummy variable is 1 when the q is low. Finally, the correlation between the two q dummy variables are also strongly negative, just as expected. Due to these high correlations, the variables are expected to be significant in many of the same industries. In the performed logistic regressions, the q variables are only significant in two to three of the industry regressions, split on four industries, hence this is in accordance with the correlation results. The q ratio is more of a company specific variable, but was included in the explanatory variables in an attempt to capture growth opportunities. The q variables do not seem to be significant in many industry regressions, hence either the growth opportunities do not have any explanatory effect on merger waves, or the q variables are not capturing what they were meant to capture. The definition of Tobin's q is flawed in multiple ways. It assumes that the replacement value of assets and market value of liabilities is appropriately proxied by book value, it ignores tax effects and it assumes that the average and marginal q are the same. The high and low q dummy variables are a more broad classification compared to the continuous q variable, hence they are not as affected by the possible measurement error in the calculation of the q (Andrade & Stafford, 2004). The relatively few significant results are in contrast to the findings by Andrade et al. (2004), who find strong significant results for the same three q variables.

8.3.1.6 Market-to-book variables

Both the MB ratio and MB ratio sd have a positive coefficient in most of the industries. The positive MB ratio coefficient is consistent with the prediction of both the neoclassical and the behavioral hypotheses. As for the positive coefficient of the MB ratio sd, this is in accordance with the behavioral hypothesis stating merger waves should be positively affected by high variation in the valuations. The correlation between the MB ratio and the MB ratio sd differs a lot, hence it is not possible to draw any definitive conclusions about the correlation between the two variables. None of the variables seem to be superior to the other in explaining the merger waves when comparing the log likelihoods. In contrast to the few significant results for the MB variables, Harford (2005) found a general positive and significant relation between the MB ratio and merger waves.

8.3.1.7 Stock return variables

The significant relation between the three-year stock return and the occurrence of a merger wave is related to the behavioral hypothesis as it is used as an indication of the overvaluation in the market. The fact that the coefficient is positive indicates that an increase in stock returns has a positive effect on the occurrence of a merger wave. The positive relation between the sd of the three-year stock return and the occurrence of a merger wave indicates that merger waves are more apparent to occur when the variation in the stock returns has been high prior to the merger wave. Both of these results are in accordance with the behavioral hypothesis described in chapter 5. These conclusions can also partly be drawn from the logistic regressions using the one-year stock return and sd, but the level of significance is not as strong as with the three-year stock return variables, which are significant in more industry regressions. As the three-year stock returns are significant in more industry regression than the one-year stock returns, it indicates that merger waves are better explained by longer periods of overvaluation, rather than more sudden overvaluation periods. This is supported by the log likelihoods where the three-year stock returns and sd have lower log likelihoods than the corresponding one-year variable.

The coefficient of the sd of the one-year stock return is negative in five industries, which is four more than the three-year stock return sd. The negative coefficient indicates that a one unit decrease in the sd of the one-year stock return in the financials industry increases the log odds of a wave with 0.0763. For the financials industry the three-year return sd is positive indicating that merger waves, at least in this industry, is positively related to high variations over a more distant past, but small variations over the recent past. However, as the sign of the coefficient of sd of one-year return in approximately equally divided between positive and negative sign, this is not the case for all industries. The difference is also shown in the correlation between the two variables, which is very weak with an average of 0.03 with approximately half of the industry correlations being negative. The coefficient for the three-year stock return sd is positive for almost all industries, and this variable is also the one, which is significant in most industries compared to all the explanatory variables. This indicates that the merger waves are more apparent to appear in times with a past of high stock return volatility, just as the behavioral hypothesis predicted.

When all variables are compared, the behavioral three-year stock return, the sd of this return and the employee growth are the variables with significant explanatory power in the most industries. In general, the number of significant cases differs from variable to variable with all the variables being significant in at least one industry. From the above logistic univariate regressions there are results in favor of both the neoclassical and the behavioral theories when it comes to the occurrence of merger waves, and all of the variables seem to have at least some kind of explanatory power on merger waves in some industries. Further more most of the explanatory variable coefficients had the sign, which was predicted by the neoclassical or behavioral theories.

8.3.2 Linear univariate regressions

For the sales, employee and EBITDA margin variables the regression results have not changed much from the logistic regression results neither for the number of significant regression results or the sign of the coefficients. The conclusions are therefore the same as discussed under the logistic regression just with the dependent variable being the number of M&A deals. The number of significant results has increased for all three q variables with the sign of the coefficients being unchanged. This indicates that the q variables are better at explaining the fluctuations in M&A activity compared to merger waves. The same seems to be the case for the MB ratio. For the MB ratio sd and all the stock return variables the results are quite similar to those of the logistic regressions, hence the conclusions are the same as previously stated.

8.3.3 Sub-conclusion on univariate regressions

The linear univariate regressions are implemented to examine whether the proposed explanatory variables have an explanatory effect on the number of M&A deals in general. The fact that many of the same variables are significant and with the same sign in both the logistic and linear regressions indicate that the two dependent variables capture some of the same movements in the merger activity. This shows that the chosen merger wave identification method is successful in capturing possible merger wave periods. The dependent variable in the linear regression has a higher variation than the dependent variable in the logistic regressions, due to the nature of the continuous and logistic variables. The fact that the linear regressions yield more significant results compared to the logistic univariate regressions might be caused by this difference in the variance of the dependent variable.

The results thus far are ambiguous as both neoclassical and behavioral explanatory variables seem to have a significant explanatory power on industry merger waves and aggregate merger activity. As for the neoclassical variables there are some patterns which recur across the different variables. In multiple regressions, both logistic and linear, the variable itself, for example sales growth, EBITDA margin or q ratio, is just as often significant as the shock variables, and in many cases within the same industries. This indicates that the merger waves and aggregate merger activity is linked to high sales growth, high employee growth, high EBITDA or high q industries, and that the shock variables are capturing these same increases. There are however also industries where the shock variables are significant without the continuous variable being significant. This indicates that the shock variables are successful in identifying big decreases as well, and that these decreases have an explanatory power towards merger waves and merger activity in general. When comparing the log likelihoods for the continuous variables and the shock variables for sales, employee and EBITDA variables, the continuous variable is the best explaining in all cases when the two shock variables are measured separately. However, if we compare the combined performance of the shock variables to the continuous variable, then the shock variable has the best explanatory power in most industries. This indicates that the shock variables are useful variables in explaining both merger activity and merger waves, just as the neoclassical theory predicted. However, neither of the two types of shock variables seems to be able to capture all the shock effects the industries are experiencing as both shock measures are significant in industries where the other shock variable is not. In general, the variable coefficients seem to be consistent with what was predicted by the neoclassical and behavioral theories, and explanatory variables from both theories are significant in multiple industry regressions.

8.3.3 Logistic multivariate regressions

8.3.3.1 Neoclassical multivariate regressions

On an overall note, none of the explanatory variables are significant in all the same industries as they were significant in with the univariate logistic regressions. This indicates that the variables affect each other, some might be complimenting each other while others might be overlapping. The fact that none of the variables are significant in all the same industries as with the logistic regressions also indicates that none of the chosen explanatory variables are superior and unaffected by the other explanatory variables. However, there is one variable, which seems to be more superior to the other variables, namely the employee growth. This is the variable with a significant coefficient in most industries, and it is also the variable with fewest changes in the significant industries compared to the univariate regressions. One explanation might be that the employee growth variable differs from the other neoclassical variables, sales, EBITDA, q and MB ratio, which are all accounting based variables. The fact that the employee growth on average has weak correlations with the other explanatory variables, most of them are below 0.07, indicate that the employee growth variable captures other industry changes than the more accounting based numbers.

In most of the multivariate industry regressions only one variable from each group is significant with some exceptions for the employee and q variables. This seems reasonable as the shock variables are identified based on the growth or ratio variables, hence there is a relatively high correlation between these variables, compared to the correlation outside the variable groups. This was also mentioned in the univariate regression discussion where some of the same group variables seemed to be significant in the same industries. An example is the communication services industry, where the addition of an EBITDA shock variable will most likely not add much explanatory power to the regression, as the EBITDA margin is significant. At the same time there is a risk of multicollinearity if these variables are included in the regression simultaneously. Multicollinearity is appearing when the explanatory variables are strongly correlated, as this will create a kind of disturbance in the data, which can affect the reliability of the statistical inferences of the data (Baesens, 2014). The previous discussion regarding the growth variables and the shock variables measuring the same industry alternations can be extended here for the multivariate regressions. The fact that most of the reduced industry regressions only include one variable, varying between the growth or ratio variables and the shock variables, supports the argument that they are measuring some of the same industry changes. For the industries only including the growth or ratio variable it could indicate that these industries are pervaded by increases rather than decreases, and that the industries including the shock variable also experiences influential decreases. The fact that the shock variable is a dummy variable and that the growth or ratio variable is a continuous variable does probably have some importance in the significant variables. I could imagine that if the shock variable was measured differently and as a continuous variable, it would probably be able to supersede the growth and ratio variables in some industries.

In general, the sales variables are not implemented in many multivariate regressions, and especially not when the q ratio is included. Both numbers are accounting based, but they do not seem to be highly correlated as the average correlation is 0.09. This indicates that the two variables should be explaining different economic changes, hence the reason behind the exclusion of the sales variables must lie elsewhere. The average correlation between the sales growth and the employee growth and EBITDA ratio is 0.25 and 0.21, respectively, and the correlations between these two variables are close to 0 on average. Hence it seems like the employee and EBITDA variables are complimenting each other, and the addition of the sales variable in regressions where these two variables are already included might not add much explanatory power compared to the risk of experiencing multicollinearity.

Another interesting case is the MB ratio and the q variables. In only one reduced industry regression is both the q ratio and the MB ratio included. This could indicate that the two variables are covering some of the same industry fluctuations, which is supported by the high correlation between the two variables. The fact that these two variables are highly correlated is not surprising when one looks at the calculations of the two variables, which are both accounting based. As for the explanatory power towards merger waves the q ratio seems to be the strongest of the two variables, both as it is included in more industry regressions, but also as the significant MB ratios seems to have changed industries after the q variables were added to the pool of explanatory variables. The industry including both the q and the MB ratio is industrials. In this industry the correlation between the two variables is 0.9471. When the correlations between two variables are this high, both variables are not expected to be a part of the reduced regression, as there is a high chance of multicollinearity. For the industrials the correlation of prediction with waves has increased compared to round three (sales, employee, EBITDA, MB), but decreased compared to round two (sales, employee, EBITDA, q). This supports the mentioned fact about the high correlation and multicollinearity between the MB and q variables.

One thing to notice with the multivariate regressions is that the absolute values of the log likelihoods have decreased compared to the logistic univariate regressions. This indicates that combining some of the chosen explanatory variables raise the performance of the models, when it comes to explaining merger waves. This is in accordance with the neoclassical theory, which predicts shocks to be causing merger waves, where the shocks can be of different character. For most of the industries the highest correlation with prediction of waves was appearing in the sales, employee, EBITDA, and q variables setting, with the employee, EBITDA, and q variables being the superior neoclassical variables, when it comes to explaining merger waves in the eleven industries. This is consistent with the described relations above. Additionally, the average correlations between the employee variables and the q and high q dummy variables are weakly positive, and the same is the case for the EBITDA and q variables correlations. Thus, these variables seem to be capturing different economic aspects, which all seem to have an explanatory power towards merger wave periods.

8.3.3.2 Behavioral multivariate regressions

As with the neoclassical variables, none of the behavioral variables are significant in all the same industries as with the univariate regressions. This indicate that the explanatory effect of the variables is affected when combined. The fact that the sd of the three-year stock return seems to be the only significant variable in most of the regressions it is included in indicate that it has a high correlation with the other variables. This is also the case with the three-year stock return, which is strongly and positively correlated with the sd of this return. This strong correlation is probably also the reason that none of the industries includes both of these variables at the same time in the reduced regressions. The sd of the MB ratio and the sd of the one-year stock return on the other hand seem to be complimenting each other as they are both significant in an industry, where they were not significant in the univariate regressions. This statement is supported by the average correlation between the two variables, which is -0.03. The sd of the one-year stock return is included in two more industries than the MB ratio sd, hence the MB ratio sd seems to be more dependent on the one-year stock return sd than the opposite way. The MB ratio is only included in two regressions, but in only one of them have the correlation with the prediction of waves increased compared to the correlation without the MB ratio. Hence the MB ratio do not seem to add much explanatory power to the behavioral multivariate regressions.

In general for the behavioral multivariate regressions, half of the regressions only include one significant variable. Some of the explanation might be due to the higher average correlations between the behavioral variables compared to the neoclassical variables, but it might also be that the behavioral variables do not have a significant explanatory power towards merger waves.

8.3.3.3 All variables

When all the variables are combined there are ten industries, where one or multiple explanatory variables are significant. The explanatory variable combination with the highest correlation of prediction with waves is in five industries only including neoclassical variables, one is only including behavioral variables and the remaining four industry regressions include both neoclassical and behavioral variables. In the five reduced regressions which include both behavioral and neoclassical variables, the three-year stock return and the sd of the one-year stock return are the most used behavioral variables in combination with the employee and sales variables. None of the previous included q or MB ratio variables are included in these five regressions indicating that these are highly correlated with the two behavioral variables. This is also the case for the three-year stock return variable, which on average is highly correlated with the q and MB variables. For four of the five regressions including both neoclassical and behavioral variables the correlation of prediction with waves have increased compared to the previous regressions. In three cases the previous best performing model was the neoclassical model and in one case it was the behavioral model. The average increase in the correlation is 0.1 across the four industries with an average correlation with waves of 0.83 for the regressions including all variables.

When the full neoclassical and the full behavioral models are compared, the neoclassical model is the one explaining the merger waves the best. In eight of the ten industries with significant variables, the full neoclassical model has the highest correlation of prediction with waves, whereas the full behavioral model only has the highest correlation in two industries. This is also shown in the average correlation of prediction with identified waves, which is 0.75 for the full neoclassical model and 0.54 for the full behavioral model.

The results of the multivariate regressions do not give a definitive result as to which variable combination explain merger waves the best. What can be concluded is that the neoclassical explanatory variables explain merger waves better than the behavioral variables in the majority of the industries, but there are also industries where a combination of the neoclassical and behavioral explanatory variables are the best performing combinations.

8.3.4 Linear multivariate regressions

8.3.4.1 Neoclassical linear multivariate regressions

As in the logistic multivariate regressions, just because a variable was significant in the univariate linear regression does not mean that it is significant in the multivariate linear regression. Additionally, for most of the variable groups, only one of the variables are included at a time, just as in the logistic multivariate regressions.

As stated in the results six industry regressions only include variables from round two; sales, employee, EBITDA and q, two industries only include variables from round three; sales, employee, EBITDA and MB ratio, and in two industries are both q and MB variables included. The MB ratio was not significant in these two industry regressions neither in round three nor in the univariate regressions. These results are similar to the results in the logistic multivariate regressions indicating that the q and MB ratio captures some of the same industry changes with the q variables being superior to the MB ratio. This is supported by the adjusted R-squared, which increases by 0.01 and 0.05 in the two regressions where both the MB ratio and q variables are significant, indicating the addition of the MB variable do not add much explanatory power when one of the q variables are already included.

An interesting difference between the multivariate logistic and linear regressions is that the sales variables are much more included in the linear multivariate models compared to the logistic models, the EBITDA shock variable is less included and the employee variables are about the same, but with an increase in the employee shock variables and decrease in the employee growth. An explanation behind the increase in the significance of the sales growth variable could be that the dependent variable is now a continuous variable, which fluctuates more than the logistic merger wave dependent variable. These fluctuations might be better explained by a continuous explanatory variable. However, the fact that the employee growth variable has decreased in number of significant cases contradicts with this hypothesis. Additionally, the number of significant neoclassical explanatory variables has increased in some industries, decreased in other industries and remained the same in the remaining industries compared to the logistic regressions, hence it does not seem to be the case that additional explanatory variables are needed to explain the additional fluctuation in the dependent variable. What does seem to be the case however, is that the sales growth variable and the employee variables seem to be significant in different industries, indicating they explain some of the same industry fluctuations. This is however not supported by the weak correlations as the average correlation between the sales growth and employee growth is 0.25 and the average correlation between the sales growth and the employee shocks is close to zero.

For the linear multivariate neoclassical regressions, the industry employee shock, MB ratio, q and sales growth seem to be the variables used in most reduced industry regressions. In most industries the regression consists of either the MB ratio or a q variable and then combined with either a sales or an employee variable.

8.3.4.2 Behavioral linear multivariate regressions

In general, all the behavioral variables, except for the three-year stock return sd, are significant in more industries than for the logistic regressions, and as a result more behavioral explanatory variables are included in each industry regression. As it is not possible to compare the adjusted R-squared from the linear regressions to the log likelihoods in the logistic regressions it is not possible to say whether it is because the behavioral variables are better at explaining the M&A deal numbers rather than the merger waves or if it just due to the fluctuation in the dependent variable.

In multiple industries the variables are significant in pairs, meaning the MB ratio and the sd of the MB ratio are significant in the same industries, and the same with the one- and three-year stock return variables. These pairs have a strong correlation on average, being 0.80 for the three-year stock return and sd of this, 0.61 for the one-year stock return pair and 0.33 for the MB ratio pair. In the regressions including one of the stock return pairs, there is expected to be a risk of multicollinearity due to the strong correlations between these variables.

8.3.4.3 All variables

In four industries the full neoclassical model has the best explanatory power, in five industries the model including all explanatory variables has the best explanatory power, and the full behavioral model is the best performing combination in two industries. For the industries including both types of variables, the adjusted R-squared has increases 0.04 on average compared to the next best performing model. This is a rather small increase in the explanatory power compared to the average R-squared of 0.50 for these five industry regressions. Overall for the models including all variables it seems like most of the previously identified significant neoclassical explanatory variables remain significant, and that in some cases one or more behavioral explanatory variables are added to the model. In four of the five industries, the neoclassical model was the one performing the best of that and the behavioral model. On average the full neoclassical model gives an adjusted R-squared of 0.44, where the full behavioral models give an average adjusted R-squared of 0.25. This shows that the neoclassical model is the best of the two models in describing the number of M&A deals, but the results are not unambiguous.

8.3.5 Sub-conclusion on multivariate regressions

The multivariate industry regressions yield different results depending on the industry and the type of model, where some speak in favor of the neoclassical hypothesis and others speak in favor of the behavioral hypothesis. The results of both types of the multivariate regressions indicate that the neoclassical hypothesis has the best explanatory power in the majority of the industries, both when it comes to merger waves but also M&A deal numbers. However, one should be careful not to make generalizations for all industries based solely on these results.

The first thing to look at is the models including all variables. In both industry types there are five industries where all variables are included, and only four industries, where the adjusted R-squared or correlation with prediction of waves increases compared to the full neoclassical or full behavioral models. As previously mentioned, in the logistic multivariate regressions, the correlation with prediction of waves increases on average with 0.10 for the four industries, and the adjusted R-squared increases on average 0.04 for the multivariate linear models. The discussion lies in whether the combination of all the explanatory variables increases the performance of the neoclassical or behavioral models to a degree, where it is noteworthy, or if the increase is more of a coincidence. For all the reduced linear multivariate regressions at least one variable has been added compared to the model performing second best. For the logistic regressions the picture is a bit more mixed with increases in the variable number is two cases, one contains the same number of variables as previously, and one industry experiences a decrease in significant variables. For the linear regressions the conclusions are rather clear, the added variables are causing the adjusted R-squared to increase, as it adds explanatory power to the regression. The added variable improves the model more than would have been expected by chance, otherwise the adjusted R-squared would not have increased. However, this increase in R-squared is rather small when it is compared to the level of adjusted R-squared for the pure neoclassical or behavioral models. As for the logistic regressions the same is the case for the two industries where the number of significant variables has increased. However, there is also two industries where the correlation of prediction with waves has increased without the number of variables increasing. In these cases, the increase must be due to the combination of neoclassical and behavioral variables, which is causing the correlation to increase rather than just and additional variable adding additional explanatory power to the already significant variables. However, this does not seem to be the general picture across the industries.

When only the full neoclassical and full behavioral regressions' performance are taken into account, the neoclassical regressions have the best explanatory power in eight industries for both the logistic and linear regressions. When the average performance of the multivariate regressions for all industries are compared, the neoclassical combination is also the best with a adjusted R-squared of 0.44 for the full neoclassical model and 0.25 for the full behavioral model in the linear regressions and a correlation with the prediction of waves of 0.73 for the full neoclassical model and 0.49 for the full behavioral model in the logistic multivariate regressions. The industries, where the behavioral variables had the best explanatory power are energy, financials, materials, and utility. These industries stand to some extent out from the rest. Different industries face different economic environments and as a result different M&A cultures. The utility sector covers companies, which provide basic amenities such as water, electricity and natural gas. These companies are often a part of the public service landscape and utilities are therefore often heavily regulated (Murphy, 2019). The energy sector cover companies producing or delivering oil, gas, and consumable fuels as well as the companies producing the energy equipment. This sector is largely driven by worldwide supply and demand (Chen, 2019). These two industries produce or provide some kind of product or service which is essential for most peoples' lives. The materials industry involves discovery, development and processing of raw materials. This sector supply most of the materials, which are used in construction work (Kopp, 2019). Due to the economic environments of the three above mentioned industries, the M&A activity in these three industries could possibly be explained by other things than growth prospects and market misvaluation. The financial industries are often left out of industry comparing studies, as there are differences in accounting standards and as the nature of the business makes it difficult to define variables, which are comparable to cash flow, capacity, etc. Because of this Andrade et al. (2004) leave out the following industries; bank and thrift, brokerage and financial services, and Insurance, which are all covered by the financials industry in this paper. The fact that these industries stand out from the remaining industries, and that their economic environment are different from the others could play a part in the multivariate industry regression results. However, the brief run-through of some of the main characteristics of the economic environments in these four industries is far from detailed enough to be able to draw any conclusions upon.

The interindustry variation in M&A activity is far from fully explained by the implemented explanatory variables. The neoclassical theory predicts waves to occur as a result of industry shocks, whereas the behavioral theory predicts a high valuation of the industry to be causing merger waves. Industry shocks can however be many things, and the sales, employee, EBITDA, q ratio, and MB ratio are just a couple. All of these variables capture shocks on the demand side, and none of them includes the supply side. This would be shocks which are expected to affect the cost of production. An example could be a technological shock. Other shocks, which could also be of importance, could be changes in industry concentration, entry barriers, foreign competition or deregulations. However not all of these variables are straight forward to measure. Hence the included variables do not cover all aspects of the economic relations and are imperfect measures of industry shocks. Also, in the behavioral theory additional variables could have been added such as management compensation and the aggregate P/E ratio. However, both types of the multivariate regressions indicated that adding a lot of additional explanatory variables do not necessarily increase the performance of the model significantly. This could for example cause problems with multicollinearity, as the industry-specific shock variables are often highly correlated.

The neoclassical model is the theory with the best explanatory power in most of the industry regressions. However, the neoclassical explanatory variables are not able to explain all the fluctuations in the industry specific M&A numbers nor in the merger waves. Some of this might be due to incomplete measures of shocks, but it might also derive from the principle behind the neoclassical theory, namely the efficient market. Market efficiency or the lack of it is a big subject within finance, hence a full discussion of this subject is out of scope of this study. As previously mentioned in an efficient capital market all market participants are assumed to have the same information and act rationally, and as a result the market prices will fully reflect all available information. Many people have studied the efficient markets and some have presented empirical evidence, which imply that the market is not efficient (O'Sullivan, 2018) (Campbell, Lo, & MacKinlay, 1997). I will not argue whether the market is efficient or not but rather consider which implications it can have for the results, if the underlying assumption of the neoclassical theory is not fulfilled. If the market is not efficient then the neoclassical explanatory variables will most likely still be of significance as to explaining big changes in M&A numbers due to the nature of the shock and related industry alternations, but not all M&A deals can be expected to be due to a change or shock in the market. As a result, the neoclassical explanatory variables are expected to be at least partly capable of predicting merger waves and also M&A deal numbers. The remaining part of the fluctuations could then be due to market inefficiency caused by different behavioral theories such as herd behavior, regret avoidance, hubris, etc. Hence if the market is not efficient, it will not be a matter of either the neoclassical or the behavioral theories as explanation to fluctuations in M&A activity and merger waves, but rather a combination of the two. The results in this study supports this as the combination of both the neoclassical and the behavioral variables increases the explanatory power in four industry regressions both when it comes to merger waves and M&A deal numbers. From the multivariate regressions including all variables it indicates that the neoclassical variables contribute with the most explanatory power, as these have the best explanatory power on their own. However, there seems to be a tendency, at least in some industries, where at least one behavioral variable is added to the already significant neoclassical variables, which increases the explanatory power of the total model. The combined neoclassical and behavioral model do still not explain all the variations in merger waves and M&A activity, however it should be mentioned that this thesis only takes the behavioral variables, which explain merger waves into account. There are several other behavioral theories which can explain a M&A deal such as regret avoidance, herd behavior, etc. How these bias and tendencies could contribute to the full model is out of the scope of this thesis to examine. The combination of the neoclassical and behavioral variables in the full reduced model seems to vary from industry to industry, hence it is not possible to conclude on how much explanatory power the neoclassical and behavioral variables each contribute with in a combined model, but the results could indicate that this depends on the economic environment of the different industries.

9. Conclusion

This thesis studies M&A activity at an industry level from 1997 to 2018. I find that there is a difference in the mean takeover month and similarly in the variance across the eleven industries, which document that there is a significant interindustry variation in the rate of M&A activity in this period. Three different approaches to detecting merger waves have been applied to the industry specific deal data. The straight-line fit model and the Markov switching regime models using AR(1) and AR(2) processes seem to be very fragile to high variances in the data, which cause them to identify a lot of waves. The number of waves identified by these methods appear to be too large considering the fact that clustering of industry specific merger waves explains aggregate merger waves as shown by Harford (2005). The number of waves identified by the simulation and Markov AR(0) models seems to be much in line with the number of aggregate merger waves. What separates the two models is the subjective choices that needs to be made in the simulation method. As a result, the Markov switching regime model using an autoregressive model of order zero, seems to be the most objective and accurate approach in explaining the industry specific M&A distribution during the past 22 years in Europe.

The univariate regression tests were implemented in the analysis in an attempt to examine whether the individual proposed explanatory variables for both the neoclassical and behavioral theories had any explanatory power towards M&A activity and merger waves. In these tests it was also examined whether the sign of the variable coefficient was as predicted by the theories. The results show that all the proposed variables had some significant explanatory power in at least one industry regression. Overall the employee growth, three-year stock return and the standard deviation of the three-year stock return were the variables, which had a significant explanatory power towards merger waves in most industries. When it comes to explaining M&A deal numbers, more variables became significant in more industries, but with the low q dummy and standard deviation of the three-year stock return being the best performing variables. The results of the univariate regressions show that the variables implemented to capture industry shocks and market misvaluation seem to have some significant explanatory power towards both M&A deal numbers but also merger waves.

The results of the logistic and linear multivariate regressions are ambiguous, as some industries are best explained by the neoclassical explanatory variables whereas other industries are best explained by the behavioral variables. However, the neoclassical model is the best performing model in seven industries and also on an overall average level, where the adjusted R-squared is 0.44 compared to 0.25 for the behavioral model and the correlation with prediction of waves is 0.73 compared to 0.49 for the behavioral model. These results indicate that industry shocks are better at predicting merger waves and M&A deal numbers than the market misvaluations. From these results, it seems like mergers and acquisitions are largely driven by industry shocks, consistent with the neoclassical theory. However, it would be unseemly to disregard the market misvaluation, consistent with the behavioral theory, as the cause of some M&A deals, as it does also seem to have some explanatory power in some industries. The behavioral theory seems to be especially prominent in the energy, financials, materials, and utility sectors, which stand a bit out from the rest of the industries. Neither the neoclassical nor the behavioral model is capable of fully explaining the industry variation in M&A activity from 2004 to 2018 with the explanatory variables tested in this study.

Furthermore, it was discussed whether the underlying assumption in the neoclassical theory of the efficient market can affect the explanatory power of the neoclassical model. The empirical results in this study mainly support the neoclassical hypothesis, but the behavioral model does also seem to have some level of explanatory power, as indicated by the behavioral multivariate regressions, but also by the increase in the adjusted R-squared and correlation with prediction of waves when all the neoclassical and behavioral variables are combined. Multiple empirical studies have proven that the market is not fully efficient, which can be one of the reasons why the neoclassical model is not capable of explaining all the fluctuations in M&A deals. Both the industry shocks predicted by the neoclassical theory and the market valuation and dispersion in this valuation predicted by the behavioral theory seems to be able to explain some of the distribution of the industry specific M&A deals between 2004 and 2018, but none of the models can explain the full distribution and variation. The discussion concludes that based on the studies of market efficiency, which do not support the efficient market, and the results from the multivariate regressions including all the tested explanatory variables, it is most likely not a question of which of the neoclassical and behavioral models that is correct, but more a matter of a combination of the two models.

10. Further research

The purpose of this thesis was to make an overall assessment of whether the neoclassical and behavioral theories can explain the fluctuations in M&A activity and merger waves in Europe. As a result, the dynamics behind the response to a single shock or variable in a specific industry was not examined. A systematic analysis of the relation between the changes in the different explanatory variables and the response in the M&A activity within the different industries might contribute to a better understanding of the merger wave phenomenon. This could possibly also add to the understanding of why the energy, financials, materials and utility sectors are better explained by the behavioral theory than the neoclassical theory and add to the discussion of the market efficiency.

As previously described, there is some limitations in the tested explanatory variables. In the neoclassical case only shocks affecting the demand side was tested, hence further research could extend the analysis of this thesis by adding more explanatory variables, preferably some which covers the supply side.

All the M&A deals were split in eleven industries. This split has already been mentioned in the delimitations section as a tradeoff between number of deals per period and industry specification. Further research could be done on a more specific industry classification, to examine a more specific link between the industry M&A activity and the industry explanatory variables.

According to the behavioral hypothesis on merger activity, merger waves should only occur for public firms and only with shares as payment method, if the overvalued shares hypothesis holds. The deal dataset covers both private as well as public companies and all payment types, hence it could be argued that the behavioral explanatory variables should generate a better result if the deal dataset only included public stock deals. As for the neoclassical theory, the firm type and method of payment is not relevant. Hence had the deal dataset only consisted of public stock deals and had the results been the same, it would speak even stronger in favor of the neoclassical theory.

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