Louvain School of Management

and NOVA School of Business and Economics

WHAT ARE THE FACTORS THAT DETERMINE THE SUCCESS OF MERGERS AND ACQUISITIONS?

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Boris Snidero

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Supervisor and reader:
Rui Silva (NOVA SBE) and Leonardo Iania (LSM)

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Abstract: Although mergers and acquisitions have been around for decades, neither managers, advisors nor researchers have been able to unlock the secrets of these transactions and what makes them successful or not. The aim of this thesis was therefore to shed light on this subject and to try to demonstrate that quantitative factors can indeed help to explain post-transaction performance. After a literature review which led to a series of hypotheses, two databases were created in order to regress on them and analyse the results. Finally, a number of interesting conclusions were drawn, and a critical judgement of this work was made.

Keywords: Directed Research; M&A; Success; Regression

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Contents

A. Introduction and research question

Mergers and acquisitions have existed for as long as the corporations themselves. Yet, managers and advisors continue to think about the most effective and efficient ways to make these deals a success. Most of these transactions fail to yield returns whether in the short-run (Jarrell and Poulsen 1989) or the long-run (King et al. 2004). The scientific community has also tried to address this issue but most of the research has focused on the strategy and more qualitative side of the story. A question thus emerges, what if pure quantitative factors could already help to assess whether a merger/acquisition will turn out to be a triumph or a disaster? The purpose of this thesis was to find answers to this question and more precisely: what are the key factors that determine the success of mergers and acquisitions?

First, a literature review was organized which entailed a review of previous works. This was useful in developing a list of hypotheses to be tested. With this list, we were then able to build a database from Bloomberg with the variables related to each hypothesis and gather deals meeting specific requirements. For example, the scope was limited to mergers and acquisitions that occurred until the end of 2017 and a distinction was made between two databases: one with American acquirers and another one without any restriction on the country of origin. The culmination of this work was the complete and stepwise multiple linear regressions on these datasets followed by the analysis of the results from which conclusions were made.

B. Literature Review

1. Methodology

Given the large number of works and articles that address M&A, a different approach was necessary regarding the literature review. A software called *Publish or Perish* was used in order to make the searches and analyse the number of citations of each document. Keywords such as "merger", "acquisition", "success" and "performance" were used, and the papers were ranked by the number of citations. Only relevant works more than 0 citations were selected. This approach resulted in a first set of 331 highly pertinent books and papers. This number was then further reduced to 137 by removing old documents with a low number of citations and others that were not peer reviewed. This methodology made it possible to select only the works widely accepted by the scientific community and use them as a primary source for this thesis. The research was also extended with the references present in the said articles. In addition to that, the website *Connected Papers* was also used to gain a better understanding of the interconnections between the selected articles and other ones.

2. Definitions

a. Mergers and acquisitions

The terms “acquisitions” and “mergers” are often used interchangeably yet there is a clear distinction between these two. The former is quite clear and is defined as one company taking a majority stake in another company’s equity. However, it is not the case with the latter which refers to the combination of two firms that can either result in a new legal entity (Singh and Singh 1971; Piesse et al. 2006) or in the absorption of one by the other (Hampton 1989; Piesse et al. 2006) The negotiating power is perceived as the determining factor between these two outcomes. When it is balanced, the first case is more likely but if it is not, then the second one will probably occur. Moreover, another nuance can be made by talking about the friendliness of these transactions. While mergers and acquisition can be seen as friendly, the term takeover refers to hostile deal and is thus differentiable from the others (Stallworthy and Kharbanda 1988; Piesse et al. 2006). Considering this, it means that the words mergers and acquisitions can be used as synonyms.

b. Success

The definition of what makes a merger or an acquisition successful was the first obstacle encountered while writing this thesis. The measurement of the success of such transactions is still debated today as there is currently no method that would provide sufficient accuracy. Indeed, the two most commonly used approaches have both strengths and weaknesses.

The first consists of an event study, a method that emerged recently with the development of econometrics. In practice, it means calculating the cumulative abnormal returns (CAR) following the announcement of a deal. As it was noticed during the compilation of the literature review, it is the most popular method used so far by scholars because of its efficiency and ease of use. However, there is no consensus about the time horizon. Some researchers decided to conduct their studies on the short-term (few days) while others opted for longer periods ranging from 3 to 5 years (Haleblian et al. 2008). A short-term perspective enables to better isolate the effect of the announcement while minimizing the noise that surrounds it. Conversely, a longer horizon increases the noise and makes it more difficult to assess the returns attributable to the deal. Another thing worth mentioning is that it also relies on the assumption that markets are efficient. This approach could only work if the price of the stock fully reflects the present and future potential of the deal. Researchers appear to have evidence to support this and claim that the market is a good predictor of post-transaction performance (Asquith 1983; Cornett and Tehranian 1992; Healy, Palepu, and Ruback 1992; Kapl and WEISBACH 1992; Haleblian et al. 2008). There is one important drawback associated with this approach though. It fails to factor in the implementation of the strategy and its related costs as the market assesses only the strategy proposed by the actors of the deal (Haleblian et al. 2008).

In an attempt to find a solution, another method was put forward by some authors. It entails the use of accounting measures to evaluate the success of a merger or an acquisition (Agrawal and Jaffe 2003; Agrawal, Jaffe, and Mandelker 1992; Cornett and Tehranian 1992; Healy, Palepu, and Ruback 1992; Krishnan, Miller, and Judge 1997; Porrini 2004; Ramaswamy 1997; Rau and Vermaelen 1998; Zollo and Singh 2004; Haleblian et al. 2008)

Although it takes better account of the implementation of the deal, it poses the same issues as using a longer window when computing the abnormal returns. It is more difficult to allocate a portion of the potential gains to the transaction itself (Haleblian et al. 2008). For example, during this period, the company may have divested part of the businesses that were failing or invested in fruitful operations that yield high returns.

In short, there is no perfect measurement of performance, let alone recognized by the scientific community. As such, both methods were used in this paper. Using the two methods helps to compensate for the drawbacks of one measure with the advantages of the other. It better captures the different aspects of these kinds of transactions and offers a more holistic view. Also, for the same reason, a short-term and long-term horizon were used during the event study to compute the cumulative abnormal returns.

3. Why do companies decide to engage into a merger or an acquisition?

There are many reasons why a company's management may decide to engage in a merger or an acquisition. Understanding these motives from the buyer's point of view can help us to grasp what these companies try to achieve and their expectations, their definition of success. However, these subjects will not be reviewed comprehensively as it is not the purpose of this paper.

a. Efficiency theory

According to Piesse et al. (2006), this theory refers to a situation where a company operating in a specific industry is not as effective as it should be, but a merger or an acquisition by another firm would solve this. Piesse et al. (2006) argue that the fact that the company is struggling is either only known amongst companies operating within the same industry (inefficiency management theory) or is public and firms in other industries are aware of it (differential efficiency theory). Moreover, the concept of synergies comes into play. Synergies can be observed when the value of the combined firm is higher than the two values taken separately. Although in opposition to Modigliani–Miller's additivity principle, it is argued that the assumptions made in this model are often unrealistic (Piesse et al. 2006). For example, synergies can arise from managerial restructuring (Leigh and North 1978) operational and financial economies of scale (Brealey, Myers, and Marcus 2001; Ross, Westerfield, and Jaffe 2002; Piesse et al. 2006) and a new culture.

b. Agency theory and management hubris

When looking for targets, a company's management may be too excited about a specific deal and this creates overconfidence. They believe that the firm they are interested in is not as efficient as it should be, but if they take control of it then they will be able to turn it around and yield high returns (Piesse et al. 2006). In other words, a target that may be bad could be perceived as a good opportunity by the management thus increasing the probability that the deal will occur. Moreover, there is also the issue of the agency theory. It refers to the situation where the management works in its interest rather than those of its shareholders (Piesse et al. 2006). In some companies, the top employees' remuneration is linked with its size and the performance of its shares. This setting incentivises the managers to expand the operations, for example by buying companies, even though it is not the best option from a financial or strategic point of view (Malatesta 1983; Piesse et al. 2006).

c. Market power

Merger and acquisition can also be seen by companies as a way of rapidly increasing their market power. This is particularly relevant to reach new regions (Leigh and North 1978; Piesse et al. 2006). For example, if a European brewing company seeks to expand its operations in Asia, it could simply buy a Chinese competitor with factories in the country to start producing and selling beers there. This motive explains why there were a lot of horizontal takeovers in the past. However, there has been an increased concern about such concentrations of market power which prompted governments to take actions in the form of antitrust laws (Utton 1982; Piesse et al. 2006)

d. Diversification

Diversification has always been seen as a way to reduce risk in most cases. This reasoning applies to financial assets but also to companies. If a firm has operations in multiple industries or geographies, it can easily offset a potential downside in one of them by an upside in another. Therefore, if a company assesses that one of its line of business may represent a risk, diversification may motivate it to merge or acquire another firm operating in an opposite segment to hedge against that risk.

e. Sending signals to the market

Assuming a strong form of the market efficiency theory, some announcements made by the management of companies can sometimes serve as a means of conveying signals to the market; this is known as the information hypothesis (Piesse et al. 2006). For example, if the management announces publicly that they intend to raise more debt, it sends a positive signal as the investors may perceive this as a sign that new profitable projects are underway. This principle is also valid for mergers and acquisitions. During the process, private information is released on which market participant can make their opinion and eventually revaluate the companies involved (Piesse et al. 2006). This phenomenon was demonstrated in several papers (M. Jensen and Ruback 1983; Sullivan, Jensen, and Hudson 1994; Piesse et al. 2006).

f. Bankruptcy avoidance and tax considerations

There are several reasons why a company may decide to acquire an enterprise on the verge of bankruptcy. One of them is the lack of bidding competition (Piesse et al. 2006). Indeed, not many firms may want to take the risk of integrating an organization that is performing very badly and is failing to meet its obligations. Therefore, it reduces the number of potential acquirers and the potential increase in the starting price. Also, the price itself may be low due to the situation the target is in (Piesse et al. 2006). The acquirer's management could then decide that it is actually a good deal and move forward with it knowing also that as a whole, a distressed target requires fewer resources (Walker and Business 1992; Piesse et al. 2006). Another considerable factor is taxation. Buying a company means integrating the target's balance sheet into the one of the acquirers. If a distressed company has deferred tax assets due to past losses, the other firm would benefit from it by reducing its tax payments. It is a trade-off between the tax savings and the risks associated with such transaction.

g. Undervaluation

Aside from management hubris, a company's management could accurately value another one and conclude that a company undervalued. Since they have a different opinion than the market, they could see that target as an opportunity to get their hands on assets, talents or markets for a cheap price. It would be therefore a no brainer for them to execute the transaction.

4. High premium paid and its consequences

In some passages in the following section, there will be occasional references to the paid premium during mergers and acquisitions. It is therefore important to understand the impact of a high premium on post-transaction performance. The previous literature showed that paying a very price results in lower gains and failure (Anslinger and Copeland 1996; Bower 2001; Datta and Puia 1995; Hayward 2002; Inkpen, Sundaram, and Rockwood 2000; Sirower 1997; Gomes et al. 2013). The main reason behind this can be found in the management's inability to recover this extra cost (Sirower 1997; M. Hitt et al. 2009). In an attempt to correct their mistake, they will engage in more risky behaviours and take actions such as restructuring part of the acquired company. It can be considered as operational synergies but when it is not planned, it is more often detrimental than beneficial (M. Hitt et al. 2009). Simply put, when acquiring a target, the goal is to pay the lowest possible premium to generate returns.

5. Previous works

As shown in appendix 1, after an extensive research, it was found that only 12 works with a similar objective were done in the past. None of these looks exactly like any other in terms of methodology. Some were also published in peer-review journals while others were written by students for their master or PhD thesis. In terms of modelling, the authors chose different measures for success and there is no consensus on the model to be used. Regarding the database itself, the authors picked different timeframes, but none was beyond 2015 so providing a more recent timeframe would already be a significant step towards the subject. The geographies of interest also vary as some of the authors decided to focus solely on a country like India or Bulgaria while others considered cross-border deals. Moreover, the number of independent variables ranges from 5 to 55 and the number of deals from 103 to 46 758. Overall, it can be said that there are definitely some gaps to be filled with this thesis and that it will certainly add value to the scientific community.

6. Hypotheses

a. National cultural distance

Before diving into details, it is important to mention the difference between national and organizational culture. The former can be defined as the mental programming of the people from a country at the collective level (Hofstede 1980) and refers more specifically to a common set of values shared among people. The latter is more about a set of routines, habits, practices and traditions (Hofstede et al. 1990). Hence, the difference with the national culture is that it can be seen in a more "physical way". As such, this paper will focus on the national culture as it would be difficult to assess the organizational culture of the companies.

Datta and Puia (1995) published an article about the impact of cross-border transactions on value creation. Using stock-based measures, they demonstrated that most of the time, these deals destroyed value for shareholders of American acquiring firms. One of the explanations found was the national cultural distance. It was argued that managers of the acquiring firms did not have enough knowledge about the other market which would result in a higher premium (Datta and Puia 1995). It was also claimed that different cultures would create administrative issues during the integration process (Datta and Puia 1995) and make it more difficult to carry out. This study was followed by another one (Schoenberg 2000) arriving at the same conclusions but, this time, using accounting-base measures of performance.

However, contrary to what was believed at that time, Morosini, Shane, and Singh (1998) demonstrated that national cultural distance may in fact improve post-acquisition performance. The reason behind this finding may be the integration of organizational routines. Indeed, some routines linked to the national culture could be considered to be more effective than others and provide a higher performance for some companies (Morosini, Shane, and Singh 1998). But, without cross-border acquisitions, it is difficult for them to integrate practices present in other countries because they lack the necessary knowledge and background. Therefore, the solution would be to acquire or merge with a company in another country that already uses these routines and transmit them to the rest of the organization (Morosini, Shane, and Singh 1998). For example, it could be done through human resource management practises, namely, training but also a good communication and involvement of people from the target company.

In an attempted to reconcile these two points of view, Stahl and Voigt (2008) conducted a meta-analysis on this matter. They concluded that there is not a right or a wrong answer to the question of whether cultural differences have an impact on post-acquisition. Instead, it is a matter of correctly assessing the degree of relatedness and the dimension of cultural differences between the two firms involved in a merger or an acquisition (Stahl and Voigt 2008). Also, the level of integration could play a role, since deals that involve a lower level could experience a higher performance. This is also mentioned in the paper written by (Vancea 2011). On a side note, it was pointed out that the Kogut and Singh (1988) index which was commonly used to assess culture distance is outdated (Shenkar 2001; Harzing and Christensen 2004; Stahl and Voigt 2008). Research should instead use other indexes such as the one built by Drogendijk and Slangen (2006) or the one developed by (Dow and Karunaratna 2006). This statement would invalidate several studies (Datta and Puia 1995; Yaakov Weber, Tarba, and Reichel 2011; Y. Weber et al. 2012) concluding that, among other things, national culture differences harm performance (Stahl and Voigt 2008). Given the higher recognition of the former study, we will adopt their results and use one of the proposed indexes when creating the variable that will be used to test the hypothesis.

In summary, the previous literature still fails to comprehend how national culture distance affect the performance of mergers and acquisitions. Therefore, the following hypothesis was tested in our work:

H1: National culture distance improves the performance of mergers and acquisitions.

b. Pre-M&A experience

As for the impact of national culture, researchers are not sure whether experience increase the performance of M&A deals.

Fowler and Schmidt (1989) found a positive correlation between the number of acquisitions and the abnormal returns after performing a stepwise regression. The arguments put forward by the authors refer to the ones developed by Kitching (1967) and Lubatkin (1983).They argued that managers do not only learn from their experience but also learn how to deal with administrative issues that may arise (Fowler and Schmidt 1989). Therefore, managers involved in past transactions would be able to increase the post-acquisition performance. However, the results obtained by this study were already in contradictions with the ones found in the past (Kusewitt Jr 1985; Fowler and Schmidt 1989).

Another study conducted by Finkelstein and Haleblian (2002) arrived at a compromise. Using organizational learning theory, they concluded that previous acquisition experience may not always result in higher levels of performance and may even destroy value (Finkelstein and Haleblian 2002). This conclusion is mainly based on the distinction between acquisition relatedness and acquisition experience. The former refers to how the target and the acquirer are similar while the latter relates only to past experience itself, whether it was in the same industry or not. With this distinction in mind, Finkelstein and Haleblian (2002) argued that if the acquirer had previous experience in acquiring targets within the same industry, then the acquisition would have positive consequences. The managers would generalize from past experience and apply their knowledge to the new deal. However, if the targets acquired in the past are not similar to the new one but managers would still generalize, then it would result in negative consequence (Finkelstein and Haleblian 2002). The other two cases would not affect the performance. Also, there is a threshold from when acquirers will start to increase their returns on acquisitions instead of destroying value (Finkelstein and Haleblian 2002). At first, the managers will tend to generalize too easily and fail to see the dissimilarities between the deals. But then, they will start to generalize the relevant aspects of the deal and discriminate the dissimilarities. Nadolska and Barkema (2007) later provided more evidence of this U-shaped relationship between the number of pas acquisitions and the performance. Overall, this means that companies that keep buying firms in the same industry will benefit the most from acquisitions in the long-run.

Laamanen and Keil (2008) provided more evidence to some extent regarding the increased performance resulting from buying companies operating in the same sector. Moreover, they added another dimension to the research by introducing the concept of acquisition rate and variability. A key factor to get higher returns on mergers and acquisitions is the development of what is known as "acquisition capability" (Laamanen and Keil 2008). It encompasses a whole range of things, from knowledge to processes but needs time and multiple acquisitions to be built correctly. Hence, a high acquisition rate and variability may undermine this process by not giving enough time to the managers to learn from previous experience and gain a certain expertise. It may even destroy value as they try to rush their analyses under the pressure (Laamanen and Keil 2008). Although, the authors agree with Finkelstein and Haleblian (2002) on the fact that prior acquisition experience can temper the effects of acquisition rate and variability. The results from the study also provide evidence that the size of the company may have some effects. Bigger companies have more resources than smaller ones to develop acquisition programs.

This led us to the second hypothesis:

> *H2: Companies that merge or acquire firms within the same sector and at a constant rate provide a higher performance.*

c. Impact of macroeconomic factors

Macroeconomic factors are important to take into account because they define the context in which the deal will occur. Kiymaz (2009) conducted a study on these factors and arrived at several conclusions. He argued that the economic environment has an impact on the premium paid by the acquirer. Indeed, a high economic risk (high inflation and high budget deficit) increases the bargaining power which could result in a lower premium and an increased post-transaction performance (Kiymaz 2009). Also, a company that wants to sell in such an environment would have very few potential buyers and would need to decrease its expectations. However, the same reasoning does not apply to political and financial risks. Markets seem to be more attentive to these types of risk and sanction transactions made in countries that are not politically and financially stable. Also, the author found that when targets operate in developed countries, the value created is higher than when they operate in emerging countries (Kiymaz 2009).

Bany-Ariffin, Hisham, and McGowan (2016) conducted another study about this matter by taking a sample from listed Malaysian companies. They tested three variables: GNP correlation between countries, the foreign economic conditions (defined through GNP growth) and the level of economic development (using IMF's classification) but only the last two were statistically significant. The former is positively correlated with value creation while the latter has the opposite effect. The explanation behind the first finding is the same as the one mentioned earlier (Kiymaz 2009). Companies are more willing to invest in countries with favourable economic conditions (Globerman and Shapiro 2005; Tuman and Emmert 2004; Bany-Ariffin, Hisham, and McGowan 2016), including lower inflation, which would give more bargaining power to the target and increase the premium paid. But, the authors also arrived at the same conclusion as (Kiymaz 2009) regarding the level of economic development. Acquiring targets in developed countries increase the value created through mergers and acquisitions.

Given the previous findings and the contradicting arguments, we provided a new hypothesis:

H3: A low credit rating of the target's country has a negative impact on value creation.

The political risk, level of inflation and level of economic development were considered to be included in the credit rating.

d. Debt level

M. Hitt et al. (1998) published an empirical study aimed at analysing some factors that could explain the success or failure of a merger or an acquisition. They used the ROA and the R&D expenses as a measure of performance. Apart from factors not relevant or already covered in this paper, they concluded that a low to moderate level of debt is beneficial (M. Hitt et al.

1998). The authors explained this result by highlighting the flexibility provided by such an amount of debt. They also contradicted previous arguments made in the past suggesting that high levels would discipline managers (M.C. Jensen 1986, 1989; M. Hitt et al. 1998).

Moreover, as mentioned in the work of M.A. Hitt, Ireland, and Harrison (2005), mergers and acquisitions have both a direct and indirect effect on debt. Such transactions generate a lot of expenses including advisory, legal and restructuring fees for example. These expenses may force companies to increase their level of debt (whether the deals are cash or stock-based) which would reduce their flexibility (M.A. Hitt, Ireland, and Harrison 2005). Debt can also have a direct effect on the financial performance of acquiring firms. As they incur more debt, the probability of default also increases and materializes in the form of a downgrade by rating agencies (M.A. Hitt, Ireland, and Harrison 2005). Consequently, the debtors require a higher opportunity cost than if the company did not make the transaction. Moreover, the extra amount of money spent on these interest expenses could have been invested directly in the operations of the firm to yield higher returns.

H4: Low to moderate levels of debt in regard to the transaction is beneficial.

e. Method of payment and M&A waves

By intuition, it is clear that the method of payment will have an impact on the success of a merger or an acquisition. If the managers of the acquiring firm believe that its stock is overvalued during a bullish market, it would seem logical for them to use it as a currency for the transaction; this is known as the market timing theory (Myers and Majluf 1984; Martynova and Renneboog 2008). As such, mergers and acquisitions waves are correlated with high market valuations (Andrade, Mitchell, and Stafford 2001; Holmstrom and Kaplan 2001; Martin 1996; Maksimovic and Phillips 2001; Savor and Lu 2009) but also caused by other factors such as liquidity, new technologies, changes in the regulation and political decisions (Martynova and Renneboog 2008). However, a question remains, why would the target's managers accept the offer if they are aware of the acquiring company's motivations? According to Rhodes-Kropf and Viswanathan (2004), it is due to human error. Indeed, when target's managers perceive that the stock offered is overvalued, they tend to correct it, but they will still overestimate the offer if the market is overvalued to a greater extend. However, they do not make this mistake when assessing cash offers (Rhodes-Kropf and Viswanathan 2004). So, these offers will occur more often when the market is undervalued. Another explanation can be found in the agency theory which states that managers do not always work towards value creation for shareholders. When the target's shares are overvalued, its managers are more prone to value-destroying behaviours in an attempt to extend the mispricing (Savor and Lu 2009). This means that they accept an offer even though they know that they will not get a good deal out of it. This theory will be later confirmed in another paper written by Rhodes-Kropf and Viswanathan (2004).

Now, whether this way of doing deals creates value or not is another matter and the focus if this work. Savor and Lu (2009) published an article providing evidence that it does create value. The acquirers benefit from market-timing by actually taking possession of fair-priced assets with stocks that are overvalued. In other words, they acquire assets at a discount (Savor and Lu 2009). This reasoning was also mentioned in a paper published by Shleifer and Vishny (2003). But, this result is nuanced by another paper that has been published by Bouwman, Fuller, and Nain (2009) based on the work of Rhodes-Kropf and Viswanathan (2004) which has already been mentioned. In this paper, the authors argue that acquisitions undertaken during times of high market valuation yield higher returns than the ones undertaken during times of low valuations. More surprisingly, this effect does not extend in the long-run. Indeed, transaction made during bullish market underperform the ones carried out during bearish market after two years, because they are believed to be of lower quality. Bouwman, Fuller, and Nain (2009) attempted to explicate this phenomenon and herding behaviour was found to be the cause of it. Amid a M&A wave, managers of companies see that there are many deals being made and it incentivises them to do the same. When the first deals of a wave caused by an industry shock (Martynova and Renneboog 2008) are perceived by the other companies to be successful, the word spreads and managers may think that it is a good idea to engage in such activities. They then make hastily decisions rather than basing them on a thorough analysis and it may even cause management hubris in some cases (Martynova and Renneboog 2008). According to the authors, this phenomenon stops only when latter mergers and acquisitions are seen as failures. This aligns with the works of Harford (2003) and Petmezas (2009) published during the same year. They explained that although transactions carried out during M&A waves provide higher performance in the short-run, it does not last in the long-run. The market realises that these deals were made in a rush by the managers, pressured by the herd, and that they were not carefully executed.

Apart from using stocks as a method of payment, previous literature has also shown that buyers that use cash as a method of payment get better result (Abhyankar, Ho, and Zhao 2005). As it seems to be widely accepted, it will not be further discussed.

H5: Stock-based mergers and acquisitions made at the beginning of a M&A wave create more value.

H6: Cash-based transactions yield better returns.

f. Relative size

Yeh and Yasuo (2002) published a study aimed at analysing the performance of mergers. In that paper, they claim that the relative size of the two companies in terms of market value is correlated with higher or lower post-transaction performance. It makes sense as acquiring smaller firms often means that the deal will be easier to execute and facilitate the integration process. Conversely, a transaction that involves a bigger enterprise will add an extra layer of complexity and make the process harder. For example, battles for dominance within the organization may arise following the deal (Gomes et al. 2013). However, this is partially false. A target that is too small may not be substantial enough to have a real impact on the financial statements of the buyer (M. Hitt et al. 2009). It could also be considered as insignificant from the perspective of the management and they would instead prioritize the core business (Gomes et al. 2013).

Therefore, there must be a trade-off regarding the relative size in order to produce the optimal performance. Generally, transactions between two firms of comparable sizes produce better performance (Ahuja and Katila 2001; Chung, Singh, and Lee 2000; Finkelstein and Haleblian 2002; Gomes et al. 2013). This allowed us to make a hypothesis about the relative size:

> *H7: Companies need to find a trade-off regarding the relative size in order to yield the highest returns.*

g. Glamour vs value acquirers

Glamour acquirers are companies that have a high price to book ratio or a high market-to -book value ratio. Conversely, value acquirers refer to firms that have a lower value for these ratios. This difference can be explained by the diverse expectations of market participants regarding these companies and their growth potential. In a study published by Rau and Vermaelen (1998), it was demonstrated that such glamour acquirers perform better in the short-run than their counterparts, but this performance does not hold in the longer term. This result is consistent whether the deal was financed with cash or equity. However, the authors used American firms for the sample so Sudarsanam and Mahate (2003) conducted an additional study on this subject by using UK companies instead. Their conclusions are in consonance with the ones of their predecessors thus confirming the difference in performance between glamour and value acquirers.

One of the explanations put forward by Rau and Vermaelen (1998) is related to the previously mentioned concept of management hubris and the extrapolation hypothesis. The managers of glamour enterprises become overconfident due to the recent gains and future expected returns which explain the high share price. In this context, they look for a target and get overoptimistic about it so they decide to move forward and seal the deal. However, the managers realise over time that they will not be able to meet the objectives because the transaction does not yield the expected performance (Rau and Vermaelen 1998). These poor results translate into the financial statements thus impacting the organization directly and its share price. Besides, there could be an information asymmetry between the managers and the market participants at the time a deal is executed. At first, the formers may be aware of a possible overvaluation of the shares, but unnoticed by the public. Later, the market realises the true value of the stocks and brings them to their actual value (Sudarsanam and Mahate 2003).

On the other hand, companies with low PE or MTB ratios have to be more careful. They need to better assess the projects they undertake and the signals they send to the market to not further reduce the share price. This principle also applies to mergers and acquisitions. Indeed, investors will be more reluctant and more prone to have a dim view of such transactions (Rau and Vermaelen 1998). They will apply more pressure on the stock at the moment of the announcement for example. But the good thing is that the managers of these firms are not subject to management hubris as it was the case for glamour stocks. Moreover, according to Lakonishok, Shleifer, and Vishny (1994) the ratios previously mentioned encapsulate the systematic errors made by the market participants. They consider value companies to be riskier than the others which is reflected if the prices of the shares. As such, investors overreact to bad news concerning value companies instead of integrating it rationally. However, the market corrects itself over time, which leads to an increase in the performance of these companies; this is consistent with the extrapolation hypothesis (Sudarsanam and Mahate 2003).

H8: Acquirers with a low PE ratio experience better performance in the long-term.

h. Nature of the bid

Takeovers can be of two kinds: friendly or hostile. In the first case, the target's management and board of directors agree on a bid proposed by an acquiring company, so that they will sell the company. In the second case, the target's management and board of directors do not come to an agreement with the acquirer, but it still decides to move forward with the transaction anyway. According to Morck, Shleifer, and Vishny (1988), each of these situations is caused by different motives. The goal of hostile bidders is mainly to restructure the target and improve its profitability. This restructuring can possibly include the management, which will therefore be reluctant towards the transaction and make it harder to complete. Actually, firing managers who are not performing well is the biggest driver of value creation (Sudarsanam and Mahate 2003). On the opposite, firms that make a friendly bid seek to generate synergies. It can only be achieved if the target's management is willing to cooperate, so it is not in the acquirer's interest to have a conflict with them.

In terms of value creation, Sudarsanam and Mahate (2003) demonstrated in an empirical study that hostile deals are actually the ones that yield the highest returns. On the contrary, friendly acquirers tend to destroy value. As such, an additional hypothesis was made:

H9: Hostile bids yield higher returns.

i. Time between signing and closing

According to the literature, the time between the announcement of a deal and its closing is critical. Since it takes longer to close the deal, the completion risk increases and it undermines the chances of success (Afsharipour 2010; Christensen et al. 2011; Thompson and Kim 2020).

Thompson and Kim (2020) decided to comprehensively investigate this subject which was mostly overlooked until now. They decided to test two hypotheses. Firstly, the diligence hypothesis assumes that if the duration between signing and closing is high, it is because the company is conducting a more detailed and thorough transactional due diligence (Thompson and Kim 2020). Although this process is costly, it could be beneficial to the firm as it is an opportunity to spot potential red flags or irregularities in the target which could potentially compromise the success of the deal. Such red flags could be overestimated revenues or risky activities for example. Based on this logic, it is then justified to delay the closing date. In fact, the lower the time spent on conducting due diligence, the lower the gains from the deal will be (Wangerin 2019; Thompson and Kim 2020). Secondly, the other proposition, the overdue hypothesis, presumes that a slow pace is explained by challenges and difficulties faced by the acquiring company (Thompson and Kim 2020). They are focusing on issues that need to be addressed, such as antitrust concerns which has the effect of extending the closing date. The authors concluded that both hypotheses are valid according to their results. A trade-off has therefore to be made between closing a deal too quickly on the one hand and taking too much time on the other hand.

H10: To achieve higher levels of performance, a trade-off has to be found regarding the time between signing and closing.

j. Free Cash Flow

In a well-known article, M.C. Jensen (1986) made a connection between the agency theory mentioned earlier and the free cash flows of a firm. The power and compensation attributed to managers are linked to the growth of the company's balance sheet and income statement. This growth is usually achieved by generating enough free cash flows that will be used to invest in new projects with the hope of yielding more returns. As such, managers will want to use as much of these free cash flows as possible to improve their situation (M.C. Jensen 1986). This is done at the direct expense of the shareholders because if a large proportion of the available cash is used for new investments, it means that the pay-out ratio will be very low. Still according to the agency theory, the managers are happy with this because distributing money to shareholders reduces the size of the balance sheet and thus their power (M.C. Jensen 1986).

Overall, it leads to a suboptimal situation where a company's management does not efficiently use cash. These wasteful expenditures can also include mergers and acquisitions. In fact, it is argued in the article that acquiring companies with a high level of free cash flows create low value at best or destroy value in the worst cases (M.C. Jensen 1986). The only solution to counter this phenomenon is the use of debt so that, it would discipline the managers into ensuring more free cash flow. However, this argument was already disputed in the "debt level" section.

H11: Buyers with a low cash balance experience better returns.

k. The financial profile of the target

One could think that the financial profile of a target will probably affect the outcome of the deal. To address this concern, Moeller and Carapeto (2012) wrote a paper about the consequences of acquiring distressed firms. As for the glamour stocks, it seems that acquiring distressed companies yield positive returns in the short-term, but it does not hold in the longer term. Some of the reasons put forward by the authors were the quick execution of the deal and the fact that the company already optimized its operations in order to get the last bits of value from them.

Taking this into consideration, the last hypothesis tested in this paper was:

H12: Acquiring distressed firm leads to lower returns in the long-run than buying healthy companies.

C. Methodology and Data

1. Main database

On the Bloomberg Terminal, there is a function called "MA". This function leads to a tab where it is possible to download a database of deals containing a set of previously selected variables such as the names of the companies involved, the relevant dates and the method of payment. Being aware of the way abnormal returns are computed, it was decided to have two databases instead of only one. The first one did not have any restrictions on the countries of both acquirers and targets (referred to as *Data 1 - Global*) while the second one only contained deals performed by American buyers (named *Data 2 - US*). Different approaches were also followed regarding each these two.

As mentioned earlier in the text, a long-time window for the event study was set in addition to a shorter one. Concerning the long-term horizon, the decision was made to take a window of five working days prior to the announcement to allow for the possibility of insider trading and two times 365 working days after that. Based on the same reasoning, a window of five working days before the announcement and five working days after seemed reasonable for the shorter timeframe. It was also necessary to take the two years' timeframe after the execution of the deal when using the accounting measure to compare the results obtained with the event study method. Therefore, the database will only have transactions that were completed until the end of 2017. On a side note, it is important to mention that no starting date was set.

In addition to the timeframe, it was also specified that the database would only contain completed M&A deals that occurred between two public companies. This was the only option available to be consistent with the measure of performance based on stock prices, but this choice was also motivated by the lack of information about private companies. Moreover, the deal size was set to above zero as a way to avoid obtaining deals with many missing values. Indeed, since it is a key variable, it was considered that if that one would be missing, there would be a higher probability that others would too. In the end, this first selection resulted in a list of 16,679 deals for *Global* and 5,997 for *US*. In the meantime, the following variables were added to this first database: the companies' names; companies' tickers; the companies' fiscal year end; the announcement and completion dates; companies' countries; the sectors; the nature of the bid; the payment type; the announced and completed deal value.

After that, it was necessary to deal with the missing values. Given the high number of transactions available, it was not deemed necessary to replace the missing values using complex models. Instead, deleting each row that had a missing value was the preferred solution as it did not affect the variability within the dataset and prevented the interference of external models. On a side note, the payment type and nature of the bid of some deals were stated as "undisclosed" so it was decided to consider them as missing values. This operation left us with 13,580 and 4,374 transactions. Moreover, there was also an issue with the dates. For various reasons, the financial data available regarding some companies on Bloomberg has been limited to specific years. Possible reasons for this include such things as write-offs and bankruptcies. It was therefore essential to have a gap of at least two years between the completion of the deal and the last fiscal year (of the acquirer) registered on Bloomberg to properly measure their performances. This was achieved in Excel by simply taking the differences between the two dates and divide the result by 365 to get it in years. It allowed us to delete the 994 rows (12,605 deals) that had a value bellow two. However, this operation was not done for *Data 2 – US.*

It also seemed important to take into account only deals that happened following the next quarter of both companies' fiscal year end. Indeed, it was necessary to ensure that the financial statements and the numbers that would be taken from these fully reflected the actual state of both firms at the time of the deal. Without going into too many details, the particularities of the database made it such that it was required to check if there was a fiscal year available for the buyer at least a quarter after the execution date. It was also needed to check if the acquirer's and target's fiscal year fell between a quarter before the deal and its execution. This left us with a list of 1435 mergers and acquisitions (88.62% lost). As a large number of transactions had to be removed, it seemed that it might also be preferable to take a different approach with *US*. That three months limit was thus extended to nine months which allowed us to retain 2,939 deals out of 4,374 (32.80% lost).

All these manipulations left us with two first clean datasets, and it was time to add more variables to them.

2. Independent Variable building

a. H1: National culture distance improves the performance of mergers and acquisitions.

As mentioned earlier, several studies disregarded the most popular index used to determine cultural distance. As such, Stahl and Voigt (2008) recommended using the one built by Drogendijk and Slangen (2006) or the one of Dow and Karunaratna (2006). However, it was possible to find a database related to Dow and Karunaratna's index but not for Drogendijk and Slangen. This posed one issue, it was not about cultural distance anymore but psychic distance. The main difference between the two is the focus of interest; one is more about the country while the other is about the individual. Cultural distance refers to values, beliefs, attitudes and traditions shared within a society, a country. Psychic distance encompasses another range of inputs like language and religion but also differences in industrial development, education and political systems. They are all gathered into one variable with a scale ranging from 0 to 10.

In the context of this paper, it was still assumed to be a fair proxy for cultural distance. Indeed, variables such as language and religion could also explain why the management of the target may experience more difficulty communicating with the acquirer's management. This lack of communication could be part of the reason why a deal would fail as an extra amount of energy would be spent in making sure that all parties understand the strategy being set and what is trying to be achieved. As such, it was decided that this index, the one developed by Dow and Karunaratna, would be used. The database was found on the website[1] and then it was just a matter of matching the countries from that excel with the one from Bloomberg. This was achieved by using the VLOOKUP() function from excel. The only challenge was that the values for the index were only given for 1995, 2005 and 2015 but there was little variation in it so taking the closest value to the completion date was enough. Moreover, some countries also had to be renamed to match the ones of Bloomberg and others like Bermuda or Liechtenstein could not be found therefore 12 rows had to be removed in *Global* but not in *US*. Finally, the continuous variable *CountriesDist* was created. The categorical variable *SameCount* was also added to just account for the fact that both companies where from the same country.

b. H2: Companies that merge or acquire firms within the same sector and at a constant rate provide a higher performance.

A simple way to know whether a deal occurred between two companies operating in the same sector would have been to use the Standard Industrial Classification code. However, these codes were created by the government of the United States and even though it was also adopted by countries outside of North America like the United Kingdom, it is not widely accepted. When trying to use the SIC codes in Bloomberg, one can realise that most of them are missing for European and Asian countries and it was therefore not usable in this paper. A solution to that was to use the industry sector name proposed by Bloomberg. After obtaining these names for each company, it was simply a matter of comparing them and make the *SameSec* variable take the value of 1 if they were operating in the same sector and 0 otherwise.

[1] Dow, Douglas. "Formative Index of Psychic Distance Stimuli". dow.net. https://dow.net.au/?page_id=618

The rate of acquisition was more complicated to model. Constance has been defined through the coefficient of variation. It is the standard deviation divided by the mean. If the outcome of this formula is bellow one, it indicates that there is a low variance in the distribution which is what we were looking for. In practice, it meant that the first database containing all deals had to be used again. All transactions were ranked by the acquirer's name and if a row had the same name as the name bellow, the difference between the completion dates was computed. Then, the OFFSET() function was used as a way to calculate the coefficient of variation progressively as each deal was executed by the same buyer instead of having one single value which would not have made sense. This gave us the *Const* feature, 1 if constant rate of acquisition and 0 otherwise.

After knowing if a deal happened between two companies from the same sector and if the acquirer was buyer at a constant pace, it was simply a matter of multiplying the two binary variables to get the *SecCons* categorical variable.

c. H3: A low credit rating of the target's country has a negative impact on value creation.

As mentioned earlier, it was considered that the inflation, level of economic development and political risk were all included in the credit rating of the countries. Even if it was not, it would have been highly correlated with the other variables. So, only that rating was needed but, it still represented a challenge. Indeed, even though these ratings should be publicly available, it turned out that it was not the case. Getting this data from Bloomberg was also found to be cumbersome as none such dataset exists. A more creative solution had to be used which consisted of scraping data from a website[2] using python[3]. It resulted in 4,183 rating distributed across different countries and years. As for the cultural distance index, the rating linked to the

[2]"Sovereigns Ratings List". countryeconomic.com. https://countryeconomy.com/

[3] Aguilar, Fernando. "Web Scraping Historical Sovereign Credit Ratings Using BeautifulSoup and Pyhton". medium.com. https://medium.com/@feraguilari/web-scraping-historical-sovereign-credit-ratings-df932f82835

closest date available had to be taken and the *Rating* variable was done. But except for a few countries, the values seemed to also be quite constant over time. On a side note, two additional rows had to be removed in *Data 1* because of a lack of data regarding two countries.

d. H4: Low to moderate levels of debt in regard to the transaction is beneficial.

This was the first value that had to be taken from Bloomberg directly using the Excel API. However, it was not possible to directly get the amount of debt that was contracted in relation to the value of the deal. Instead, the debt to asset ratio of the year prior the transaction and the year after were used and then compared to get the *DiffDebtToAsset* variable. This was achieved by using the BDH() formula and the "TOT_DEBT_TO_TOT_ASSET" field. Some values were missing but it was deemed preferable to delete all the rows with missing values once the other variables from Bloomberg would have been extracted.

To avoid taking the difference between two ratios, we also decided to add the buyer's debt before and after the transaction, then divide it by the completed value of the deal to have *DebtToVal*. Since the transaction value was already in the databases, it was only necessary to take the book value of debt through the BGH() formula and the "SHORT_AND_LONG_TERM_DEBT" field.

e. H5: Stock based mergers and acquisitions made at the beginning of a M&A wave create more value.

As mentioned earlier, mergers and acquisitions waves are correlated with the overvaluation of the market. But, we have also seen that the timing also have an impact in the value creation potential. When looking for precise starting and ending dates for mergers and acquisitions waves, no reliable sources were found, or they were giving different values. Some of them also mentioned a new wave that would have started in 2011. So, it was decided to plot a graph of the number of deals per year with the database that was already available and make a decision based on that.

As observable in appendix 2, although some data are probably missing for the period before 1998, it can still be inferred that a wave started that year and ended in 2000 because of the dot-com crisis. Then, another one began in 2004 before coming to an end in 2007. After that, it becomes less clear whether an additional wave occurred or not. In this case, only the 1998-2000 and 2004-2007 waves was taken into consideration. A new dummy variable called *StockWave* was created and took the value of 1 (0 otherwise) if the deal was fully or partially paid with stocks and occurred in 1999, 2000 or 2004.

f. H6: Cash based mergers and acquisitions yield higher returns.

As mentioned before, the payment type was already available in the first database downloaded from Bloomberg and we renamed it *PayType*.

g. H7: Companies need to find a trade-off regarding the relative size in order to yield the highest returns.

The values for the *RelatSize* variable were also directly taken from Bloomberg using the Excel API. Taking the market cap would have been the easiest solution and would have produced the least missing values but not considering the net debt would have been a mistake given the importance of it. So, the BDH() formula was used with the following field "CRNCY_ADJ_CURR_EV" as an input to have the values for both the target and the buyer at the time of the publication of their respective financial statements. Having the enterprise value at the time of the announcement would have skewed the result because it would have been influenced by the abnormal movement in the stocks prices. Then, the acquirer's enterprise value was divided by the one of the target.

h. H8: *Acquirers with a low PE ratio experience better performance in the long-term.*

To test this hypothesis, data was also taken from Bloomberg with the Excel API using a similar method as for the other variables. “PE_RATIO” and the acquirer’s ticker served as inputs in order to get the values for the *PER* feature. In order to have an additional ratio to compare it with, the price to book ratio was added with the name *PtoB* after getting the values from the BDH() formula and the “PX_TO_BOOK_RATIO” input.

i. H9: *Hostile bids yield higher returns.*

This variable was already present in the main database but took many values: Friendly; Hostile; Hostile to Friendly; Unsolicited; Unsolicited to Friendly and Unsolicited to Hostile. All the bids that went from one type to the other were simply replaced by the final one in *Data 1* but not in *Data 2* to see if there was difference. For example, in the dataset, “Unsolicited to Hostile” was replaced by “Hostile”. This gave another dummy variable called *Bid* that took the value of 1 when the bid was hostile and 0 otherwise.

j. H10: In order to achieve higher levels of performance, a trade-off has to be found regarding the time between signing and closing.

Since the completion and the announcement dates were already available, the *Speed* feature was simply defined as the difference between the two dates in days.

k. H11: Acquiring companies with a low cash balance experience better returns.

In order to test this hypothesis, the cash ratio of the target at the time of the transaction seemed to be the best solution. It was also taken from Bloomberg by using the “CASH_RATIO” field in the BDH() formula. With these values, a continuous variable named *CashRatio* was created. Following the same reasoning as for *PER*, the free cash flow margin, or *FCFMarg*, was also included thanks to the “FREE_CASH_FLOW_MARGIN” field.

l. H12: Acquiring distressed firm leads to lower returns in the long-run than buying healthy companies.

The Altman Z score was originally invented in 1968 by Professor Edward Altman. The goal of the model at that time was to assess the distress of publicly traded manufacturing companies. This was achieved by performing a multiple discriminant analysis using a set of financial ratios such as: Working Capital on Total Assets (X1); Retained Earnings on Total Assets (X2); EBIT on Total Assets (X3); Market Value of Equity on Book Value of Liabilities (X4) and Sales on Total Assets (X5) which were the one retained in the end (Altman, Haldeman, and Narayanan 1977). This model turned out to be correct as it had a precision of 95% one year before bankruptcy and even 82% two years before. It has been later updated to also leave the possibility to evaluate SMEs, private companies, but more importantly, nonmanufacturers. This update is similar to the previous model but without the last variable, Sales on Total Assets. Indeed, this ratio was considered as more industry specific and so it made sense to remove it and reassess the coefficients for each variable.

So, the model went from this, for manufacturing companies:

$$Z = 1.2(X1) + 1.4(X2) + 3.3(X3) + 0.6(X4) + 0.999(X5) \tag{1}$$

To this one:

$$Z" = 6.56(X1) + 3.26(X2) + 6.72(X3) + 1.05(X4) \tag{2}$$

With the variables remaining the same as the ones previously mentioned.

Overall, it is safe to say that it represents a good measure to evaluate the level of distress of the targets we are interested in at the moment of the merger or acquisition. It includes different ratios that are all relevant in regard to the objective of this paper. On the practical side, Bloomberg already provides us with this metrics and just have to be selected in the BDH() formula with the field “ALTMAN_Z_SCORE” which gave us the *AltZ* feature.

A simpler ratio, debt-to-equity, was also added as more debt in regards to equity increases the probably of default. After, inputting the "TOT_DEBT_TO_TOT_EQY" field, the *DtoE* continuous variable was included in the databases.

3. Dependant variable building

A. Return On Asset

As for the accounting measure, Thanos and Papadakis (2012) decided to do a literature review of 36 studies that used accounting ratios as a measure of performance for mergers and acquisitions. Out of these 36, 17 used the return on asset to assess the success of such transactions. It was also the one used in this paper given its popularity and the fact that it leads to less biased results compared with other ratios like return on equity and return on sales (Meeks and Meeks 1981; Thanos and Papadakis 2012). In practise, the acquirer's ROA of the year preceding the deal was subtracted from the ROA of two years after the completion of the merger or acquisition, giving us *ROADiff*. These values were also taken from Bloomberg using the "RETURN_ON_ASSET" field. If the outcome was superior to zero, it meant that there was indeed an improvement following the transaction which is what we were looking for.

In addition to *ROADiff*, we also created *ROAMean* which was the difference between the mean of the two previous years and the two years after the completion. This choice was motivated by the fact that the return on asset of a specific year could have been influenced by external factors, independent of firm's activities. So, taking the mean was a way to mitigate these effects.

B. Cumulative abnormal returns

Although it is common practise to use software such as Stata or R Studio to perform event studies, it was not the end goal of this thesis, so it was decided to go on with Excel. Also, the stock prices were extracted from Bloomberg directly to Excel with the BDH() formula and the

"PX_LAST" field so using the same software provided consistency and reduced the probability of making mistakes.

The estimation window was defined as ending 30 days before the announcement to be sure to avoid any effect linked to it while the starting point was 300 working days prior that point. A trade-off had to be found between the ideal amount of data to download and the actual capacities to extract such amount. Regarding Bloomberg, the daily limit is set to 500,000 hits meaning that it would be possible to get only 500,000 stock prices per day. But the limit that was of most concern was the monthly one. Indeed, it is not disclosed by the service provider and there is actually no way to get an idea about when this limit would be reached. The fact that the terminals were shared with other students also had to be considered in order to not compromise someone else's work by using too much of the daily and monthly limits.

Regarding the event window, a first one was set to start five working days before the deal and five working days after, for a total of eleven days. A second window was then created using the same starting point but ending 2*365 working days after. Although the starting date was different than the one used with the return on asset, it was still useful to try to match the ending points to allow for an indirect comparison of the results obtained with the two methods.

To compute the abnormal returns (AR) and the cumulative abnormal returns (CAR), the market model seemed to be the most appropriate approach:

$$R_{i,\tau} = \alpha + \beta_i R_{m,\tau} + \epsilon_{i,\tau} \tag{3}$$

Where E($\epsilon_{i,\tau}$) = 0 and Var($\epsilon_{i,\tau}$) = σ_ϵ^2

$$AR_{i,\tau} = \dot{\hat{\alpha}} + \widehat{\beta_i} R_{m,\tau} = \hat{\epsilon}_{i,\tau} \tag{4}$$

$$\overline{AR_\tau} = \frac{1}{N} \sum_{\tau=\tau_1}^{N} AR_{i,\tau} \qquad \text{and} \qquad \overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_1} \overline{AR_\tau} \tag{5}$$

However, the fact that there was not a particular geographical area of interest posed a problem. The market model is often based on an index ($R_{m,\tau}$) such as the S&P500 but in the first case with *Data 1 - Global*, using an American index for companies from outside North American would not have made sense. A solution had to be found. In an article, Park (2004) addressed this issue and came to the conclusion that a using a world market model was necessary. He argued that taking a regular market model in a multi-country setting would lead to an overestimation of the returns. Taking that into consideration, the MSCI world index was employed to calculate the expected normal returns.

In the second case, *Data 2,* things were simpler as we did not have to worry about a multi-country model since all the acquirers were from the United States of America. So, the S&P500 index serve as the reference for the market model.

Finally, the abnormal returns for each security and event window were added together (equation 5) so that the *Short* and *Long* continuous variable would be created.

4. Summary of data lost

At each step of the above-mentioned methodology, some part of the data was lost.

Regarding the first database, as shown appendix 3, an important number of mergers and acquisitions had to be removed from the dataset due to lacking data. The biggest drop occurred when only the transactions that took place during the quarter following the end of both companies' fiscal years were kept. Three was also a lot of missing values present in the data downloaded from Bloomberg which further reduced the number of rows. At first sight, it may not seem reasonable to drop such a big number of deals (98.48%) but this operation was essential to guarantee to quality of the data needed for the linear regressions.

As for the second database (appendix 4), only a small percentage of deals (5.40%) were kept in the end. Extending the limit from three months after the end of fiscal years to nine months allowed us to increase to final number of rows kept but missing values in the data from Bloomberg still forced us to remove a lot of deals.

5. Data exploration and transformation

Once the data was gathered and cleaned of missing values, it was time to explore what was in it and eventually transform them with R before performing the complete and stepwise regressions. It is also worth mentioning that the stepwise regressions were based on the Akaike Information Criterion.

A. Numerical Variables

After a first look at both databases, it was noticed that there were extreme values present in both of them. To solve this, the outliers had to be removed according to the quartiles of each distribution and the same rows were deleted in the categorical features.

Moreover, during the literature review, two variables came out as having a potential non-linear relationship with the variable of interest: the relative size of both companies involved in the deal and the speed of the transaction. Indeed, it was concluded that a trade-off had to be found regarding these two variables. To confirm that, the *ROADiff* variable was plotted against each variable in each dataset and a trend line was also added.

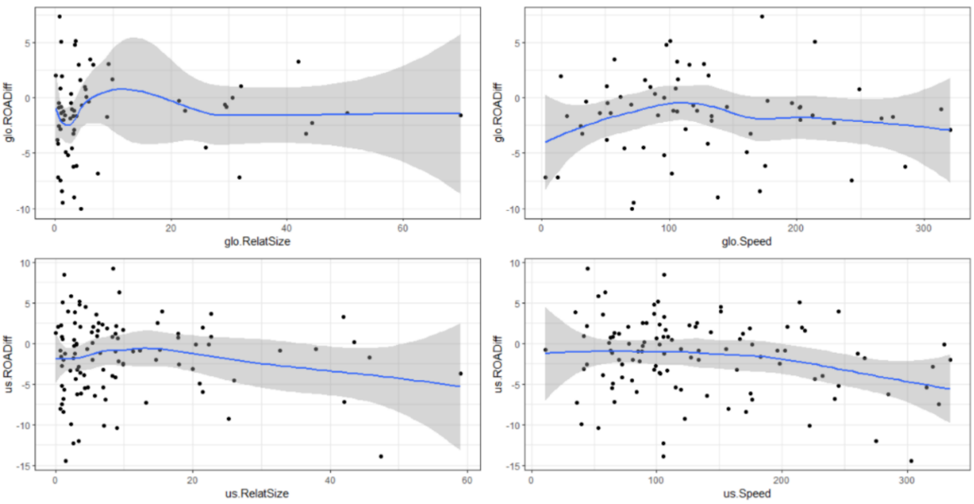

Figure 1: ROADiff against RelatSize and Speed

From the graphs, there was no longer any doubt about the non-linear relationship. Regarding *RelatSize*, values around 10 seemed to be generate the best results for both databases while the values around 2 had the opposite effect. The same phenomenon was also observed with *Speed* as *ROADiff* peaked around 100 days. Therefore, as a way to keep the multiple linear regression model, the features were split into 9 different intervals and then considered as categorical variables instead of numerical ones.

In addition to that, *CountDist* had to be dealt with. When the two companies had the same country of origin, a zero was put in the column but since the other values were continuous and higher than one, it created a skewed distribution. This skewness was also intensified by the fact that there was not a majority of cross-border transactions which translated in a high number of occurrences for the zero value. So, this feature was also converted into a categorical one.

After having dealt with *RelatSize*, *Speed* and *CountDist*, the rest of the numerical variables were examined:

	DiffDebtToAsset	PER	PtoB	FCFMarg	CashR	DtoE	AltZ	DebtToVal	ROADiff	ROAMean	Short	Long
Min.	-12.010	5.010	0.420	-13.020	0.010	0.640	0.960	-1.640	-10.030	-12.700	-0.170	-3.480
1st Qu.	-3.310	10.690	1.200	-0.250	0.120	26.960	1.950	0.080	-3.230	-3.790	-0.040	-0.740
Median	0.670	18.490	1.900	4.030	0.270	53.670	2.670	0.580	-1.240	-1.280	0	-0.040
Mean	0.620	18.980	2.130	3.670	0.360	64.730	3.130	3.280	-1.520	-0.590	0.010	-0.190
3rd Qu.	4.610	23.420	2.750	7.830	0.540	83.640	4.230	1.790	0.790	0.630	0.050	0.310
Max.	13.110	45.820	5.450	20.060	1.200	222.330	7.120	38.990	7.350	33.530	0.220	2.830
Var	32.550	97.520	1.370	38.740	0.090	2, 520.910	2.130	60.750	13.770	37.760	0.010	1.180
Skew	-0.120	0.850	0.880	-0.030	0.930	1.180	0.710	3.190	-0.210	2.680	0.380	-0.220
Kurt	-0.470	0.170	0.320	0.680	-0.060	1.200	-0.120	10.030	-0.150	12.700	0.380	1.690

Figure 2: Summary statistics for Data 1 - Global

	DiffDebtToAsset	PER	PtoB	FCFMarg	CashR	DtoE	AltZ	DebtToVal	ROADiff	ROAMean	Short	Long
Min.	-12.990	4.660	0.480	-8.210	0	0.010	0.960	-1.430	-14.400	-12.190	-1.130	-3.350
1st Qu.	-2.740	12.640	1.420	2.060	0.070	22.180	2.940	0.050	-4.290	-3.890	-0.060	-0.910
Median	1.040	17.710	2.080	4.170	0.300	45.330	4.040	0.400	-0.930	-0.880	0	-0.210
Mean	1.470	19.580	2.510	4.840	0.370	58.260	4.080	0.500	-1.610	-1.100	-0.030	-0.330
3rd Qu.	6.370	24.910	3.190	7.010	0.570	84.200	5.010	0.840	1.500	1.320	0.060	0.260
Max.	17.500	61.610	7	18.310	1.440	184.750	8.510	2.380	9.230	18.690	0.420	2.090
Var	45.030	99.710	2.140	26.340	0.110	2, 156.450	2.950	0.450	21.140	23.510	0.050	1.110
Skew	0.110	1.340	1.030	0.350	1.090	0.800	0.390	0.470	-0.450	0.600	-3.110	-0.500
Kurt	-0.490	2.750	0.390	0.380	1.010	-0.310	-0.190	0.480	0.180	2.820	12.480	0.510

Figure 3: Summary statistics for Data 2 - US

It was inferred from the two tables that some of the explanatory variables did not follow a normal distribution. While the *DiffDebtToAsset* and *FCFMarg* features looked fine, the others seemed to have a highly skewed distribution indicating that they were not close to a normal one. They all had value greater than 0.7 (except *AltZ* and *DebtToVal* in *US*) with the maximum being 3.19 from the *DebtToVal* feature in the first database. That variable also had the highest kurtosis value indicating a very steep curve. However, these skewed distributions could be explained by the nature of the data itself. All came from financial statement of companies where in most cases, it is easier to achieve a low value than a high one. For example, having a high price-to-equity ratio would mean that the company managed to convinced investors that their company's stock was worth a lot but convincing them the otherwise would not have been difficult. The same reasoning applies to the cash ratio. Not many companies are able to generate or willing to keep surplus of cash so most firms find themselves on the left side of the distribution. High variance is also an attribute of this type of data as it reflects the complexity and volatility of companies' operations. As such, the debt-to-equity ratio had a high variance in both cases, reflecting the various capital structure adopted across different sectors.

But even though there is an explanation behind the skewed distribution, the Shapiro-Wilk test had to be performed as a way to confirm the non-normality (Shapiro and Wilk 1965):

$$W_n = \frac{\sum_{i=1}^{[n/2]}(X_{n-i-1} - X_i)a_{in}}{[(n-1)s^2]} \tag{6}$$

Where a_{in} is given in a table and s^2 is the variance of the sample.

These were the p-values obtained:

	DiffDebtToAsset	PER	PtoB	FCFMarg	CashR	DtoE	AltZ	DebtToVal
P-value	0.899	0.001	0.002	0.267	$5.714e-05$	$7.679e-05$	0.005	$1.821e-13$

Figure 4: P-values for the Shapiro-Wilk test (Data 1 - Global)

	DiffDebtToAsset	PER	PtoB	FCFMarg	CashR	DtoE	AltZ	DebtToVal
P-value	0.493	$2.262e-06$	$1.472e-06$	0.019	$1.719e-07$	$5.767e-06$	0.084	0.009

Figure 5: P-values for the Shapiro-Wilk test (Data 2 - US)

A p-value lower than 0.05 (or another confidence level) implies the rejection of the normal distribution hypothesis and it was the case for all variables except *DiffDebtToAsset* in both datasets as long as *FCFMarg* in *Global* and *AltZ* in *US*. So, the features with a value lower than 0.05 had to be transformed in order to be sure to the model would be robust against heteroskedasticity.

Regarding *Global*, the box-cox transformation (Box and Cox 1964) was applied to the features having values higher than zero (*PER, PtoB, CashR, DtoE and AltZ*):

$$y(\lambda) = \begin{cases} ((y+\lambda_2)^{\lambda_1} - 1)/\lambda_1 & if\ \lambda_1 \neq 0 \\ \log(y+\lambda_2) & if\ \lambda_1 = 0 \end{cases} \tag{7}$$

Where λ is an estimated parameter (see appendix 6 for the values obtained).

The Yeo-Johnson transformation was applied otherwise (*DebtToVal*):[4]

$$\varphi(\lambda, y) = \begin{cases} ((y+1)^{\lambda} - 1)/\lambda & if\ \lambda \neq 0, y \geq 0 \\ \log(y+1) & if\ \lambda = 0, y \geq 0 \\ -[(-y+1)^{2-\lambda} - 1]/(2-\lambda) & if\ \lambda \neq 2, y < 0 \\ -\log(-y+1) & if\ \lambda = 2, y < 0 \end{cases} \tag{8}$$

Where λ is an estimated parameter (see appendix 6 for the values obtained).

Concerning *US*, the Box-Cox transformation had to be applied on *PER*, *PtoB*, *CashR* and *DtoE* while the Yeo-Johnson transformation on *DebtToVal* and *FCFMarg* (see appendix 7 for the lambdas obtained)

These operations enabled us to improve the p-values of the Shapiro-Wilk test:

	PER	PtoB	CashR	DtoE	AltZ	DebtToVal
P-value	0.477	0.614	0.331	0.996	0.515	0.004

Figure 6: P-values for the Shapiro-Wilk test after transformation (Data 1 - Global)

[4] "YeoJohnsonTransformer ". feature-engine.readthedocs.io. https://feature-engine.readthedocs.io/en/latest/transformation/YeoJohnsonTransformer.html

After the transformation, all variables had a p-value higher than 0.05 except *DebtToVal* which has a value of 0.004. The null hypothesis stating that the data is normally distributed was therefore rejected again. The continuous variable had therefore to be converted into a categorical one.

	PER	PtoB	CashR	DtoE	FCFMArg	DebtToVal
P-value	0.825	0.504	0.002	0.224	0.031	0.0484

Figure 7: P-values for the Shapiro-Wilk test after transformation (Data 2 - US)

Data 2 - US proved to be more difficult to handle as three variables still had a p-value below the 0.05 threshold. To keep a maximum number of numerical variables, it was decided that *DebtToVal* would be kept as it was while *CashR* and *FCFMarg* would be converted into categorical variables.

Finally, it was interesting to make some remarks about the dependant variables. Consistent with the previous literature, all means and medians were negative except for the shortest timeframe. It indicated that a majority of mergers and acquisitions did not produce returns for the acquirers. This outcome highlighted again the need to understand these transactions and what makes them failures or a success.

On a side note, correlograms were made in order to check the absence of collinearity between the independent variables which is one of the assumptions of the models used. They are provided in appendix 8 and 9 but all variables were kept.

B. Categorical Variables

As observed in appendix 10, the categorial variables were heavily unbalanced as for the numerical ones. It was mostly problematic for two variables. The first one was *StockWave*. There was only a small minority of values taking 1 which probably interfered with the models. In the case of *Bid*, there were simply no “Hostile” left meaning that no conclusions about *H9* could not be drawn. Fortunately, it was not the case with the second dataset (see appendix 11).

D. Empirical Results

1. Description of the results

First of all, all the models were robust as shown in appendix 14 to appendix 17 for the Breusch Pagan test (Breusch and Pagan 1979)[5]:

$$LM = nR^2 \sim X^{2(k)} \tag{9}$$

$$F = \frac{R^2/k}{(1-R^2)/\,(n-k-1)} \sim F(k, n-k-1) \tag{10}$$

Give the high number of results, each model was broken down by dataset and the stepwise regressions were separated from the others. Regarding the interpretations, we were aware that transforming the numerical variable would make the sign of the coefficients much more difficult to interpret. But, by looking at the graphs of the transformed variables (appendix 12 and appendix 13) it was still possible to gauge whether it was going in the right direction or not.

Complete regression from the first database, *Data 1 - Global* (the variables not discussed were not significant at any level; see appendix 18 for the detailed results):

- *PER*: only the coefficient for the *Long* regression was statistically significant at the 0.05 level. The negative sign provided evidence in favour of *H8*.
- *CashR*: none of the coefficients were statistically significant at all conventional levels but at the 0.2 level, the ones of the *ROADiff* and *Long* regressions became interpretable. In the former regression, the coefficient had a small negative value while it was positive in the latter case but still had a small value.
- *AltZ*: there was one significant and positive value for the coefficient in *ROADiff* thus showing results in accordance with *H12*.

[5] Zaiontz, Charles. "Breusch-Pagan Test". real-statistics.com. https://www.real-statistics.com/multiple-regression/heteroskedasticity/breusch-pagan-test/

- *FCFMarg*: the coefficients were statistically significant at the 0.01 level in the *ROAMean* and *Long* regressions. In one case, it was negative and positive in the other, but both had small values indicating that the effect may not be clear.
- *SameCount1*: only the coefficient in the *Long* regression was significant at the 0.05 level. It had a low negative value thus providing further evidence in favour of *H1*.
- *SameSec1*: the only significant value was found in *ROADiff* but was negative which contradicted the hypothesis made about deals between two companies in the same sector, *H2*.
- *Const1:* when taking a confidence level of 0.2, the coefficient of the *Short* regression became significant and had a small negative value.
- *SecCons1:* only the coefficient in the *Long* regression became significant at the 0.2 level. It had a positive value close to 1 thus supporting weak evidence in favour of *H2*.
- *Rating:* in the *ROAMean* regression, most of the coefficients were statistically significant at the 0.05 level at least. However, it did not provide evidence to support the hypothesis that acquiring companies in countries with a low rating increases the post-transaction performance. Indeed, all the values were positive and within the same range. But in the *Long* regression, it was not the case. The "BBB-" and "B" ratings had really low and negative values while being significant. When extending the confidence level to 0.2, the "AA-" and "AA+" ratings also had negative values but much higher that than the "BBB-" and "B". Therefore, contrary to the *ROAMean* regression, *Long* provided some evidence to support the hypothesis.
- *PayType:* the coefficients were the most statistically significant in the *ROAMean* regression and in *ROADiff*. In both cases, the values were positive and close to one regarding payments involving stocks which indicated that *H5* tended to be true.

- *CountDist*: in the *Long* regression, all the coefficients were statistically significant at the 0.05 level at least. However, all the values were low and negative while the highest was in the [0.889:1.78] interval. On the other hand, there was one significant coefficient regarding the *ROADiff* regression that had a high positive value for the [2.67:3.56] interval thus providing mix results about whether culture distance is beneficial in terms of value creation.
- *Speed*: as for *CountDist* in the *Long* regression, all values were negative and significant, at the 0.1 level at least regarding *ROAMean*. But, the highest value was the one linked to the [34.7: 66.4] interval which provided evidence in favour or *H10*. None of the other coefficients from the other regressions were significant.
- *RelatSize*: *Short* is the only regression where no coefficient was significant. Regarding the other three regressions, the results were mixed. In *Long*, the statistically significant coefficients were highly negative for the highest interval and then were getting more positive as the relative size would decrease with the highest being the [21:28] break. But, the exact opposite phenomenon were observed in the regressions using an accounting measure since as the maximum value was linked to the [62.9:70] break in both cases.
- *DebtToVal*: contrary to the relative size, the maximum value was for the coefficient situated in the highest interval [34.9:39] in the *Long* regression and it was significant at the 0.01 level. Interestingly, the other effect was observed again in *ROAMean* as the coefficient for that break was the lowest and negative when considering a confidence level of 0.2.

Overall, all regressions except *Short* showed interesting results while having acceptable adjusted R^2 ranging from 0.349 to 0487. The others provided mixed results for some categorical variables but also provided strong evidence to support a few hypotheses. The last regression, *Long*, showed results in favour of *H1*; *H3* and *H8* while the accounting-based regressions showed promising findings to support *H5, H10 and H12* but contradicting results regarding

H2. Finally, *Short* was not useful as no coefficient was statistically significant at the conventional levels and had a negative adjusted R^2.

These results were then compared to the ones obtained with the second dataset, *Data 2 - US* (the variables not discussed were not significant at any level; see appendix 19 for the detailed results):

- *DiffDebtToAsset*: even though no conclusions could be drawn from the first database, the coefficient from the *Short* regression was significant at the 0.01 level and positive although close to zero. It was also interesting to notice that when allowing for a higher confidence level, the coefficient was also positive in *Long* but not in *ROADiff*. Overall, it was difficult to interpret these results.
- *DebtToVal*: the findings for this variable supported *H6* as the coefficient in *Long* was significant at the 0.05 and was negative. When extending the level to 0.2, the value in *Short* was also negative. This was the first time that evidence in favour of *H6* was found since the results of the previous dataset were inconclusive.
- *PtoB*: the results regarding the abnormal returns-based regressions were promising as both values were negative while being significant thus providing additional evidence to support *H8*.
- *DtoE*: one value was significant and was found in the *Short* regression. Although close to zero, it still had a positive value indicating that *H12* was not correct.
- *SameCount1*: in line with the previous findings, most of the coefficients were statistically significant and all of these had very low negative values indicating that transactions between companies from the same country is detrimental to value creation. That time, the accounting-based regressions also provided further evidence.
- *SameSec1*: also in line with the previous results, the only statistically significant coefficient was negative and was in *Short*. Again, this meant that *H2* could be wrong.

- *SecCons1*: when extending the confidence level to 0.2, the coefficient was significant and positive thus in favour of *H2* which came in contradiction with the findings related to *SameSec1*.
- *Rating*: the results were also mixed as most of the significant values where in *ROADiff* but all negative and within the same range which was not possible to interpret.
- *StockWave1*: the coefficient in *Short* was negative while being significant which contradicts *H5*. On the other hand, if the confidence level was increased to 0.2, the value in *Long* was significant and positive.
- *PayType*: the only statistically significant coefficient was in *ROADiff* and related to payments in cash and stocks but was negative therefore showing some evidence against *H6*.
- *CountDist*: surprisingly, apart from *Short*, most of the coefficient were statistically significant but they all had very low negative value. This was particularly the case for the higher range. This meant that there was a high chance that *H1* was wrong to some extent.
- *Speed*: the only significant value was found in the first regression. It was negative and related to a high range [269:302] meaning that deals that take time to settle would produce lower returns (*H10*).
- *RelatSize*: the only significant values were found in *ROADiff* and *ROAMean*. In the former, there was a positive coefficient linked to the [5.9:11.8] break and another very low negative value related to [47.2:53.1] which was also the case in *ROAMean*. These results provided strong evidence to support *H7* and if compared with the other database, the optimal range seemed to be located between 5.9 and 14.
- *FCFMarg*: according to the results of *ROAMean*, there seemed to be a trend showing that higher values lead to lower returns as the coefficients were the most negative in the higher ranges. This was in line which what was stated in *H11*.

- *CashR*: the same thing happened with this variable but that time, there was also a statistically significant value in *Long*. It still showed the same trend therefore providing further evidence for *H11*.

To summarize, there were still mixed results about some hypotheses, namely *H1, H2, H3, H5* and *H6*. The stock-based regressions brought additional evidence in favour of *H8* and new evidence for *H11* and *H12* (with *Short*) while the accounting-based models showed the same results regarding *H10* but new proof towards *H7 and H11*. More importantly, the findings suggested that *H1* was true but that the proxy used to measure the cultural distance was not right. Indeed, the binary variable *SameCount* was linked with higher performance while *CountDist* had the opposite effect.

Then, it was time to analyse the stepwise regressions (based on Akaike Information Criterion). But since the regressions will all the variables were analysed in detail, it was sufficient to make general comments about the stepwise regressions.

Regarding the stepwise regression on *Data 1 (*see appendix 20 for the detailed results), *ROADiff* provided additional evidence to support *H11* as the coefficient was negative and significant, but also *H12*. The results contradicted the statements made in *H2* as it was the case for the complete regression on *Data 1* and *2*. Moreover, it became clear that payments with stocks (*H5*) allows the acquirers to generate the most returns. More interestingly, there was a positive and statistically significant coefficient regarding *CountDist* that was linked to the [2.67:3.56] interval while there was a negative value for a higher break. This could potentially mean that American and non-American acquirers behave differently towards culturally distant targets (*H1*). Then, for *RelatSize*, there were high positive and significant values for the highest intervals which was not in line with the previous findings. However, it did provide sufficient proof to support *H4* because the highest interval of the *DebtToVal* variable had a very low negative coefficient.

ROAMean also provided more proof to support *H11* as long as *H5* and showed the same phenomenon regarding *H1* but the interval changed from [2.67:3.56] to [1.78:2.67]. All the significant coefficients for *Speed* were negative but the maximum was related to the [34.7:66.4] interval so it still supported *H10* to some extent. Concerning *RelatSize* and *H7*, there were mixed results because there were two intervals linked with high positive values, both the lowest and highest while one in the middle was linked to a negative coefficient. There was less confusion about *H4* as it showed more proof that the hypothesis was true.

Again, not many things could be inferred from *Short* except that there was evidence indicating that *H12* was true but it contradicted the findings from the complete regression on *Data 2*. It may be because American acquirers have a different attitude towards distressed firms. Moreover, it also showed proof against *H2*.

Finally, *Long* showed promising results towards *H2*, *H8* and *H11*. More importantly, there were for the first-time results in accordance with *H1*. As the cultural distance increased, the value for the coefficients were more positive while still being significant. The model also provided strong evidence is favour of *H7* since the highest interval had the most negative value while [21:28] had a positive value related to it. However, it there was opposite evidence regarding *H4*.

The last step was then to analyse the outcome of the stepwise regression on *Data 2 (*see appendix 21 for the detailed results). There were less statistically significant coefficients so only general interpretations were made. Thanks to *Short*, there was for the first-time evidence to support *H3* and also evidence against *H5*. *H4* and *H8* were also proved to be true according to the results according to the stock-based models. There was also more proof regarding *H11* thanks to the accounting-based models. More importantly, the interval [5.68:6.5] was significant and highly positive thus indicating mixed results again regarding *H1* compared to the other models. No clear conclusions were drawn regarding *Speed* and *RelatSize* even though the highest intervals had significant and negative values.

As mentioned in the beginning this thesis, these results have to be considered in a holistic view. In this context, combining the findings of the accounting and stock-based model thus makes sense. Not really making a direct distinction between *Data 1 - Global* and *Data 2 - US* was also not an issue given the reasons that led us to build two different datasets and the fact that some deals in *Data 1* are also present in *Data 2*.

E. Conclusions

The aim of this thesis was to identify the key success factors of mergers and acquisitions. The literature review made it possible to identify several reflexion paths in order to put forward a series of hypotheses which were then tested. Building the databases to test these was probably the biggest challenge faced during the writing of this work. Indeed, it was difficult to keep as much transactions as possible while maintaining a sufficient quality to ensure good outcomes regarding the complete and stepwise regressions.

Overall, the results still enabled us to confirm a series of hypothesis and reject others. While it was clear that transactions between two companies from the same country of origin lead to lower performance, the effect was still difficult to measure in terms of cultural distance since the models showed mixed results. They also indicated that the chosen index to measure this effect was probably not the right one. But this is not a surprise since it is still a topic of debate in the current literature and no clear conclusions have emerged from it, even less which index to use. The exact same thing also happened regarding the rating. The values for each rating were often negative and within the same range. Furthermore, the models demonstrated that acquiring financially strong targets with low cash balances was beneficial to the buyer as it was expected from the literature review although the first statement was not valid for American acquirers. Regarding the share price, targets with a lower price-to-equity ratio or price-to-book proved to generate higher returns than their counterparties but this was only observed in the models based on cumulative abnormal returns. The stocks were also a determining factor in the method of payment according to the accounting-based regressions. Although, it was not possible to make conclusions about using stocks during M&A waves, it was clear that stock-based deals was more effective in terms of value creation. As for the debt, lower amounts compared to the value of the deal lead to the same positive outcome which is explained by less pressure on the financials of the company and more flexibility. Moreover, the nonlinear relationship between the dependant variables and *Speed* as long as *RelatSize* was observed although no optimal interval could be found for both. Some evidence still indicated a range from 5.9 to 14 for the relative size.

Contrary to the previous hypotheses, one proved to be wrong and is the one about acquiring companies at a constant rate within the same sector. No reason can explain this phenomenon and further investigation on this particular subject could be useful.

Finally, we were not able to make conclusions for the effects of using cash as a method of payment which came as a surprise and the nature of the bid either because the results obtained were not conclusive or because of a lack of data. It was also not possible to observe the short-term effect of the *PER* and *PtoB* as long as the debt.

F. Critical setbacks and implications

Concerning the data itself, the cultural distance index was a challenge as there was not an ideal proxy to be found. The choice to use the Dow and Karunaratna's index may have skewed the results and could be the reason why the effect of this variable was not clear. In addition to that, the quality of the data from Bloomberg was not as high as expected since there were many missing values which has resulted in a reduction of the size of both databases and the number of observations for the regressions. Ideally, one should use as much inputs as possible so that the model can better capture all the effects present in the dependant variables.

Another possible issue concerned the dependant variables. The return on assets was not adjusted for the industry as no such data covering the period of interest was found. Adjusting the ROA would have enabled to consider the external trend in the industry and better isolate the effects of the transactions. Other measures such as the Economic Value Added could have been useful as well.

Regarding the stock-based measures, there was also a lot of uncertainty surrounding the abnormal returns due to the way of calculating them which may have made it difficult for the models to accurately assess the effect of each variables. More importantly, the cumulative abnormal returns were not tested as no widely accepted test was found. More importantly, deleting even more observations would have been detrimental to the results of the models. Moreover, the inconclusive results from *Short* were surprising. One of the reasons behind that could be that the event window was not short enough and captured movements in the stock prices that were not linked to the transaction.

Finally, only quantitative factors were considered in this work. Communication or governance could also impact the performance of a merger or an acquisition and is probably the reason why the adjusted R^2 never went above 0.6. The variance that was not explained by the models probably came from these factors that were not considered.

This work highlights the need for further research as a model to perfectly explain the success factors of mergers and acquisition could not be found.

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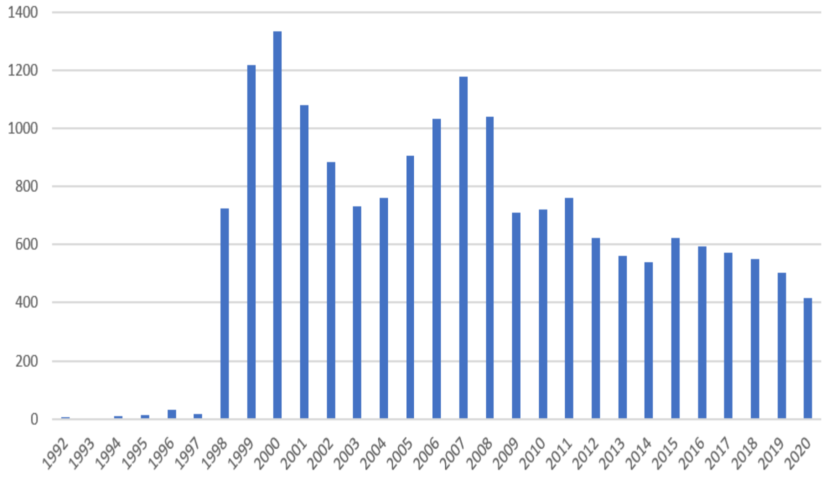
H. Appendices

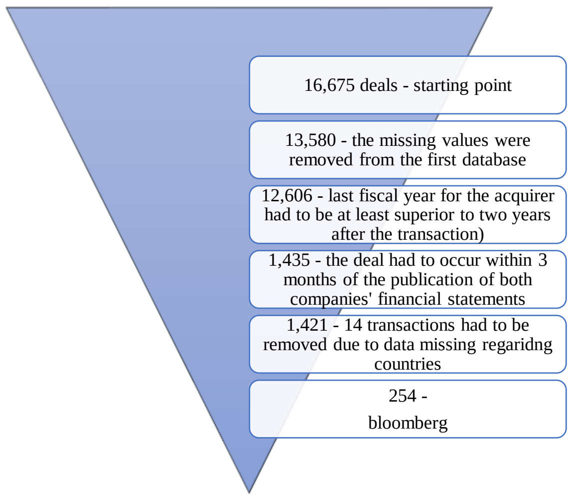
Appendix 1: Summary table of previous works

Type	Author(s)	Title	Definition of success	Model	Number of indep variables	Number of obs	Timeframe	Geography
Published Paper	Kusewitt, J.B. (1985)	An Exploratory Study of Strategic Acquisition Factors Relating to Performance	Accounting measure (change in ROA) and market return	Linear Regression and each variable was taken individually	7	138	1967-1976	Cross-border
Published Paper	Changqi, W. & Ningling, X. (2007).	Determinants of Cross-Border Merger & Acquisition Performance of Chinese Enterprises	Accounting measure (change in ROA)	Linear Regression	5	165	2000 - 2006	Cross border (focus on China)
Published Paper	Nam, C. G., Pae. Y., & Yi, J. (2008).	Prediction model of post-merger performance	Accounting measure (additional required ROE)	Linear Regression and Exponential Prediciton Model	5	807	2003 - 2004	US
Published Paper	Lankova, S. (2014).	Main factors of success in mergers and acquisitions' performance	Not specified	Factor analysis	26	103	1996 - 2014	Bulgaria
Master thesis	Martins, E.S. (2015)	M&A in Portugal: an event study	CAR	CAAR	6	114	1997 - 2014	Portugal
Ph.D Thesis	Balogh, C. (2016).	Analysis of factors determining success of cross-border mergers & acquisitions	CAR and BAHR	Linear Regression	55	175	2000 - 2000	Cross-border
Master thesis	Asensio, T. N. (2016).	Merger and acquisitionsin small to medium sized enterprisesA Quantitative study at the link between pre-merger preparation and post-merger success.	Accounting measure (Total Asset CAGR)	Linear Regression	4	608 SME's	2009	European Union
Master thesis	Diederen, X. (2016).	Factors influencing deal success in M&A:The impact of merger spread and cultural differences on deal success in mergers and acquisitions	Not specified	Logistic regression	15	2998	1995 - 2015	Cross border (focus on the US)
Published Paper	Leepsa, N. M., & Mishra, C. S. (2017).	Predicting the Success of Mergers and Acquisitions in Manufacturing Sectorin India: A Logistic Analysis	Accounting measure (EVA)	Logistic regression	10	407	2000 - 2008	Cross border
Published Paper	Alhenawi, Y., & Stilwell, M. (2017).	Value creation and the probability of success in mergerand acquisition transactions	TQ, EVTA, EVSL, and CAR	Stepwise regression + logistic + MDA	27	454	1998 - 2010	US
Master thesis	Kolar, A. (2018)	EVA as a performance measure of M&A A performance evaluation and comparison study	Accounting measure (EVA)	Linear Regression and each variable was taken individually	6	870	2002-2013	US
Published Paper	Tanna, S., Youssef, I., & Nnadi, M. (2019).	Probability of mergers and acquisitions deal failure	CAR	Probit regression	18	46 758	1977 - 2012	Cross-border

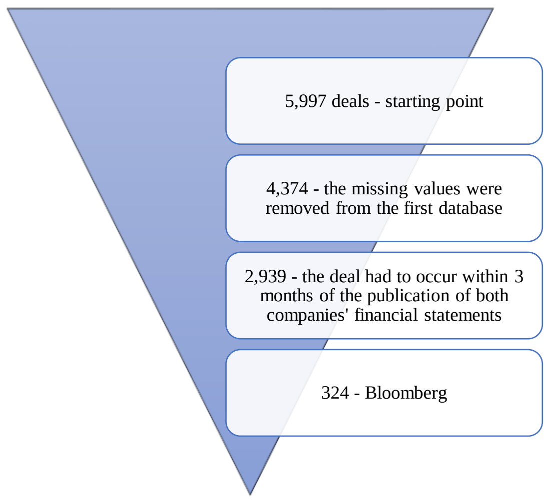
Appendix 2: Number of mergers and acquisitions per year from 1992 to 2020 according to data from Bloomberg



Appendix 3: Data 1 – Global: Number of deals left after each step



Appendix 4: Data 2 – US: Number of deals left after each step



Appendix 5: Description of the variables

- *CountriesDist*: continuous variable that measured the psychic distance between the countries of the acquirer and the target.
- *SameCount:* binary variable that took 1 if both companies have the same country of origin; 0 otherwise.
- *SameSec*: binary variable that took 1 if the acquirer made previous transactions in the same industry; 0 otherwise.
- *Const*: binary variable that took 1 if the acquirer had a constant rate of acquisition in the past; 0 otherwise.
- *SecCons*: binary variable that took 1 if the acquirer had a constant rate of acquisition in the past; 0 otherwise.
- *Rating:* categorical variable that represented the credit rating of the target's country.
- *DiffDebtToAsset*: continuous variable that represented the difference between the acquirer's debt to asset ratio of the year prior the transaction and the year after.
- *DebtToVal*: continuous variable that represented the difference between the acquirer's debt before and after the transaction divided by the completed value of the deal.
- *StockWave*: binary variable that took the value of 1 (0 otherwise) if the deal was fully or partially paid with stocks and occurred in 1999, 2000 or 2004.
- *PayType*: categorical variable that represented the method of payment.
- *RelatSize*: continuous variable that represented the acquirer's enterprise value divided by the one of the target.
- *PER*: continuous variable that represented the price-to-equity ratio of the target.
- *PtoB*: continuous variable that represented the price-to-book ratio of the target.
- *Bid*: categorical variable that represented the nature of the bid.

- *Speed*: discrete variable defined as the difference between the two announcement and completion dates in days.
- *CashRatio*: continuous variable that represented the cash ratio of the target.
- *FCFMarg*: continuous variable that represented the free cash flow margin of the target.
- *AltZ:* continuous variable that represented the Altman Z-Score of the target.
- *DtoE*: continuous variable that represented the debt-to-equity ratio of the target.
- *ROADiff*: continuous variable that represented the difference between the acquirer's ROA of the year preceding the deal and the ROA of two years after the completion of the deal.
- *ROAMean*: continuous variable that represented the difference between the mean of the ROA of the two previous years and the two years after the completion.
- *Short*: continuous variable that represented the cumulative abnormal returns of the acquirer during the shortest event window.
- *Long*: continuous variable that represented the cumulative abnormal returns of the acquirer during the longest event window.

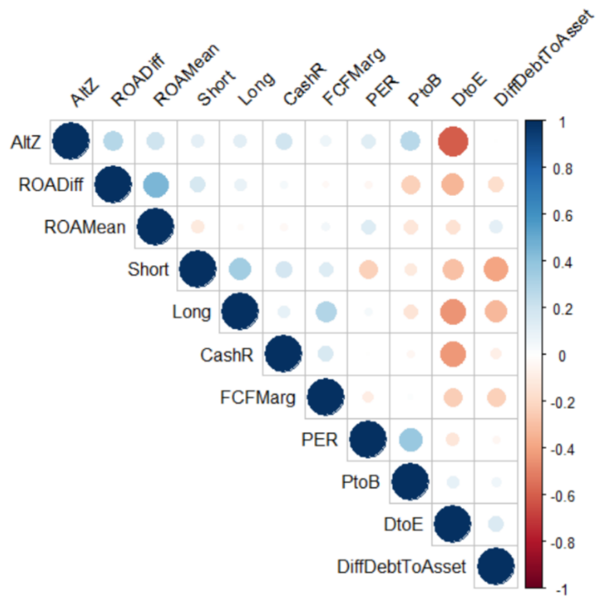
Appendix 6: Lambdas obtained with Box-Cox and Yeo-Johnson transformations (*Data 1 - Global*)

	PER	PtoB	CashR	DtoE	AltZ	DebtToVal
Lambda	0.2	0.2	0.3	0.4	0.2	N.A.

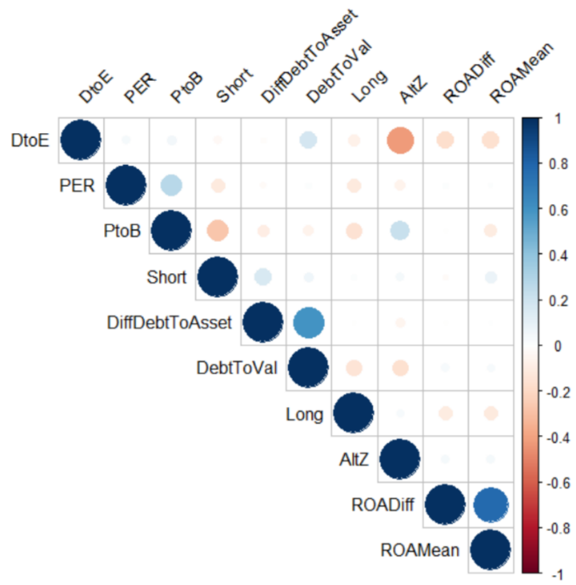
Appendix 7: Lambdas obtained with Box-Cox and Yeo-Johnson transformations (*Data 2 - US*)

	PER	PtoB	CashR	DtoE	DebtToVal	FCFMarg
Lambda	0.1	0.1	0.3	0.4	N.A.	N.A.

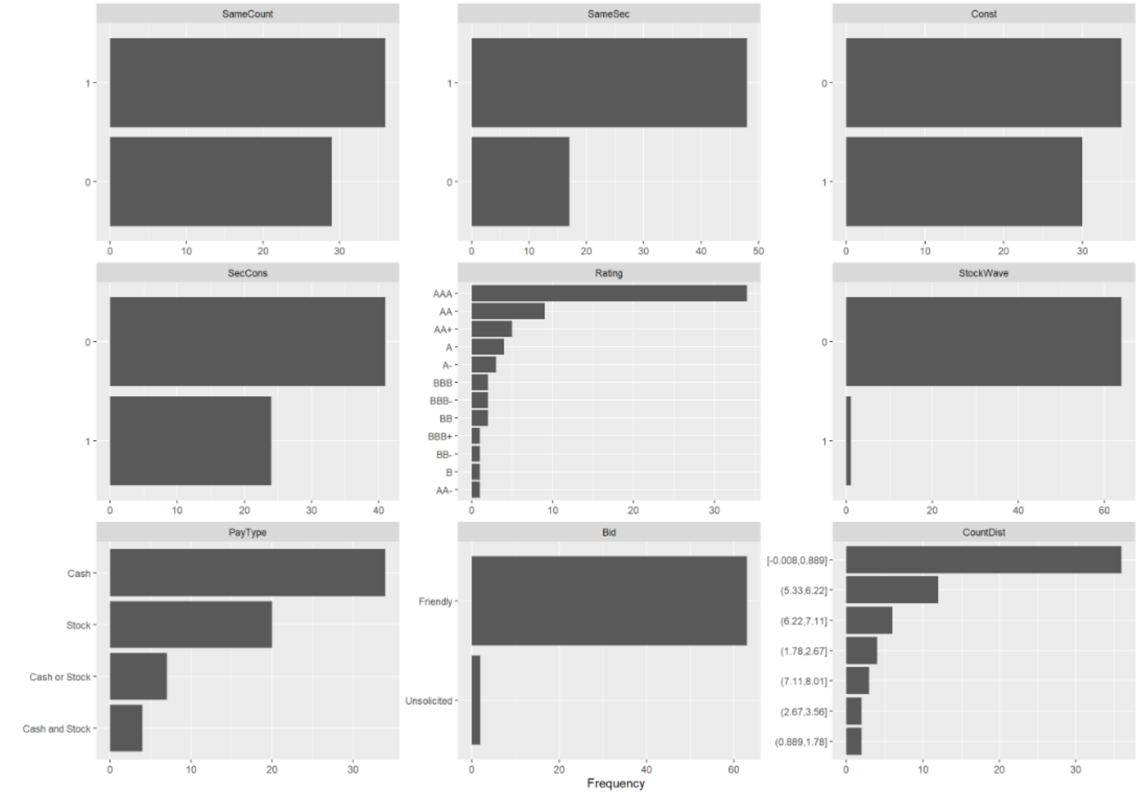
Appendix 8: Correlogram regarding numerical variables (*Data 1 – Global*)

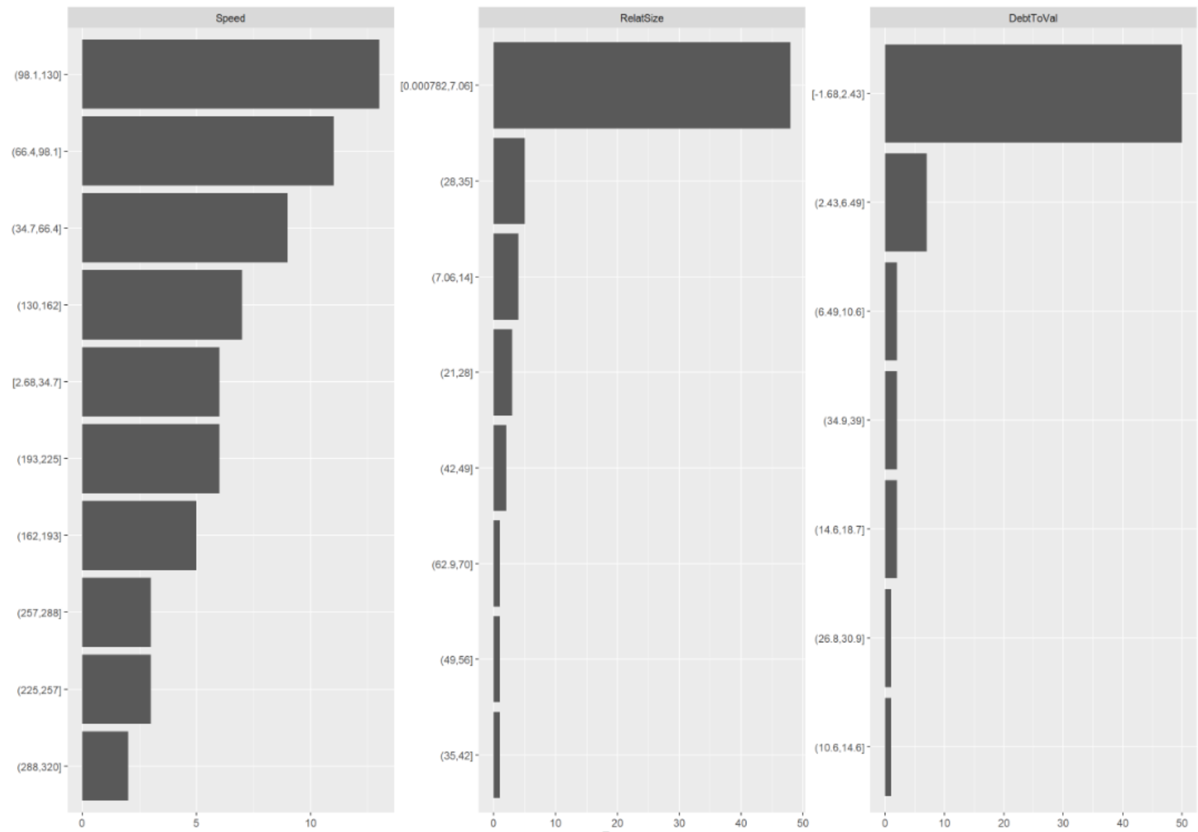


Appendix 9: Correlogram regarding numerical variables (*Data 2 – US*)

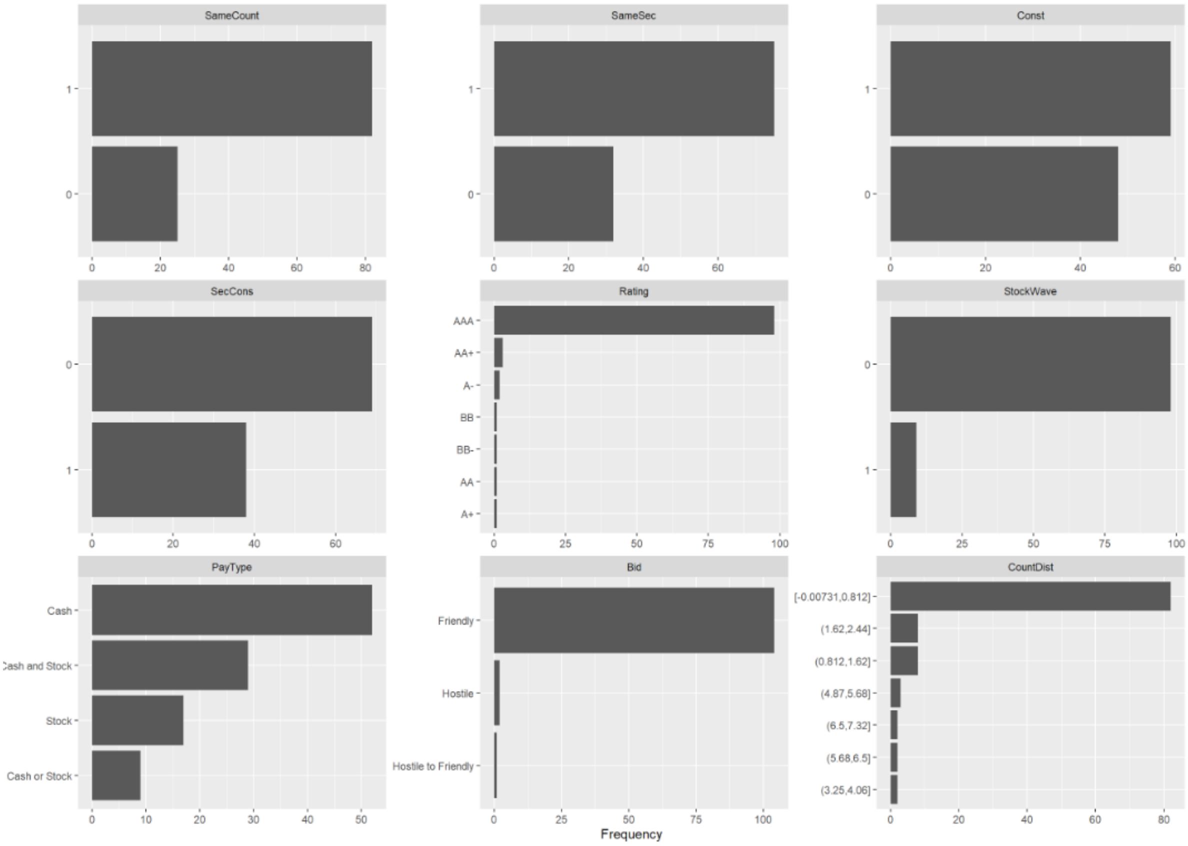


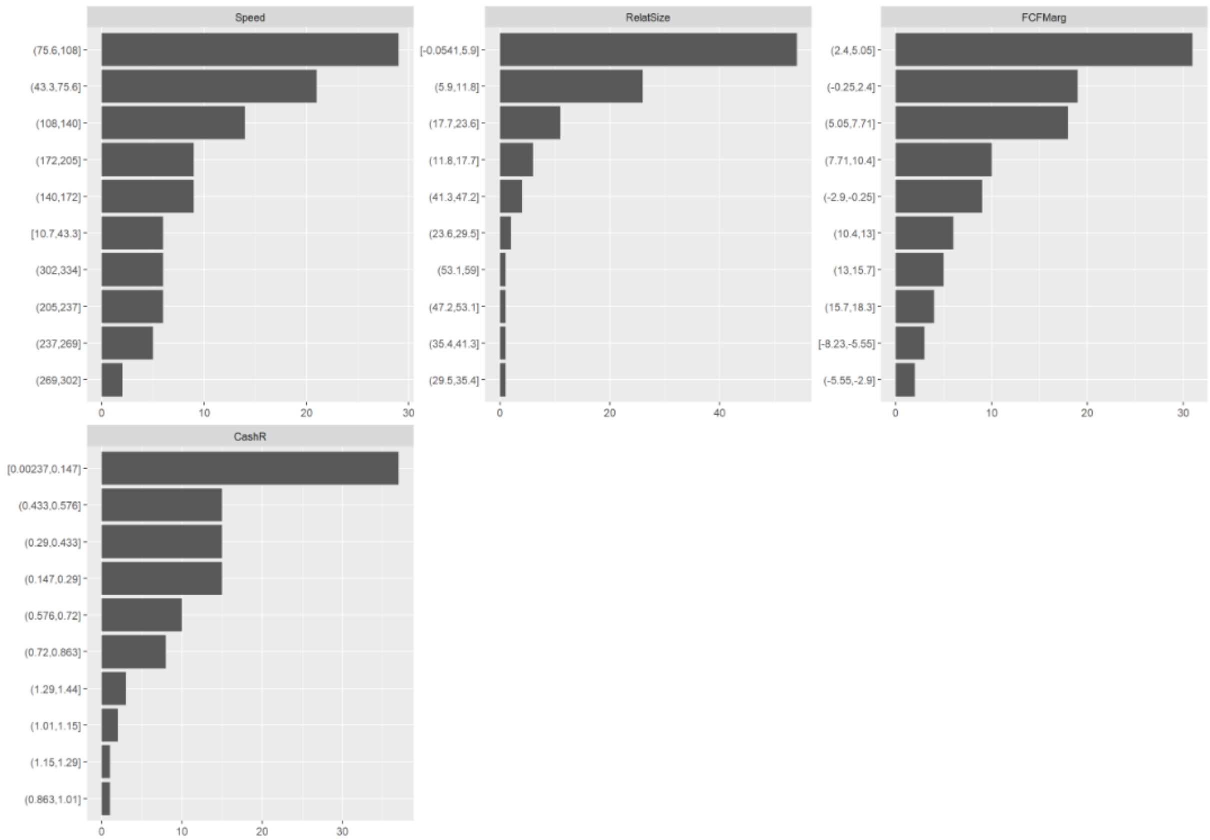
Appendix 10: bar charts of categorical variables (*Data 1 – Global*)



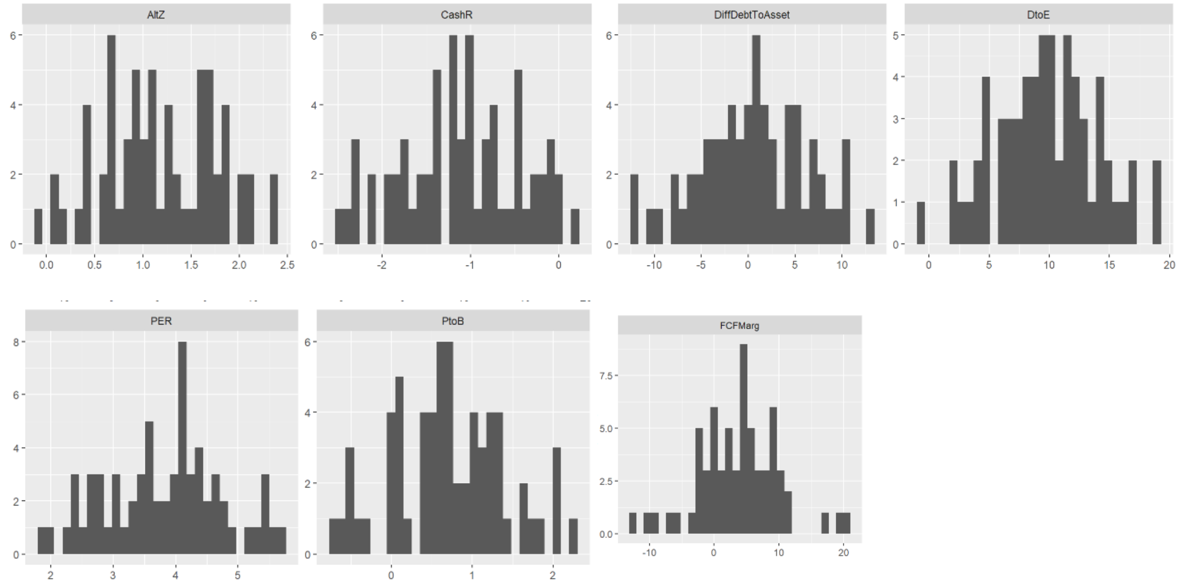


Appendix 11: bar charts of categorical variables (*Data 2 – US*)

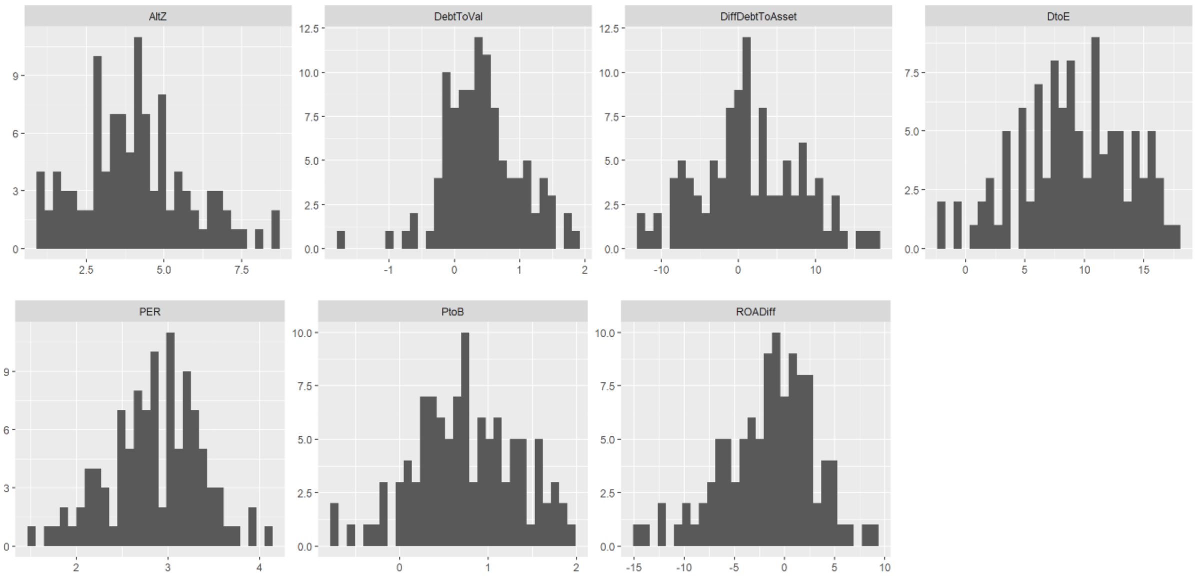




Appendix 12: Histograms of the transformed numerical variables (*Data 1 – Global*)



Appendix 13: Histograms of the transformed numerical variables (*Data 2 – US*)



Appendix 14: P-values for BP test complete regression (*Data 1 – Global*)

	ROADiff	ROAMean	Short	Long
P-value	0.212	0.467	0.328	0.802

Appendix 15: P-values for BP test stepwise regression (*Data 1 – Global*)

	ROADiff	ROAMean	Short	Long
P-value	0.249	0.687	0.552	0.916

Appendix 16: P-values for BP test complete regression (*Data 2 – US*)

	ROADiff	ROAMean	Short	Long
P-value	0.571	0.155	0.545	0.520

Appendix 17 - P-values for BP test stepwise regression (*Data 2 – US*)

	ROADiff	ROAMean	Short	Long
P-value	0.688	0.092	0.238	0.564

Appendix 18: Complete regression (*Data 1 – Global*)

	Dependent variable:			
	ROADiff	ROAMean	Short	Long
	(1)	(2)	(3)	(4)
PER	0.151	0.127	0.004	-0.227^{*}
	$p = 0.324$	$p = 0.445$	$p = 0.922$	$p = 0.073$
PtoB	-0.260	-0.177	0.034	-0.126
	$p = 0.220$	$p = 0.436$	$p = 0.497$	$p = 0.437$
CashR	-0.242	-0.023	-0.017	0.205
	$p = 0.172$	$p = 0.903$	$p = 0.680$	$p = 0.143$
DtoE	-0.076	0.016	-0.021	0.030
	$p = 0.207$	$p = 0.799$	$p = 0.150$	$p = 0.510$
AltZ	0.676^{**}	0.337	-0.001	-0.389
	$p = 0.046$	$p = 0.329$	$p = 0.985$	$p = 0.126$
DiffDebtToAsset	-0.002	-0.008	-0.005	0.007
	$p = 0.933$	$p = 0.764$	$p = 0.448$	$p = 0.708$
FCFMarg	-0.024	-0.049^{*}	-0.001	0.033^{*}
	$p = 0.303$	$p = 0.073$	$p = 0.840$	$p = 0.089$
SameCount1	1.672	1.142	0.431	-4.499^{**}
	$p = 0.409$	$p = 0.603$	$p = 0.377$	$p = 0.013$
SameSec1	-1.238^{***}	-0.581	-0.097	0.196
	$p = 0.005$	$p = 0.159$	$p = 0.274$	$p = 0.489$
Const1	-0.344	-0.749	-0.223	-0.459
	$p = 0.547$	$p = 0.241$	$p = 0.121$	$p = 0.311$
SecCons1	0.299	0.818	0.196	0.867
	$p = 0.663$	$p = 0.286$	$p = 0.246$	$p = 0.124$
RatingA-	0.697	3.217^{**}	-0.139	-1.299
	$p = 0.588$	$p = 0.038$	$p = 0.653$	$p = 0.209$
RatingAA	0.687	3.303^{**}	-0.064	-0.935
	$p = 0.614$	$p = 0.044$	$p = 0.844$	$p = 0.386$
RatingAA-	1.082	4.051^{**}	-0.011	-1.870
	$p = 0.494$	$p = 0.034$	$p = 0.977$	$p = 0.146$
RatingAA+	0.931	3.808^{**}	-0.028	-1.393
	$p = 0.468$	$p = 0.017$	$p = 0.928$	$p = 0.178$
RatingAAA	0.669	3.578^{**}	-0.142	-1.287
	$p = 0.619$	$p = 0.030$	$p = 0.660$	$p = 0.233$

RatingB	0.825	2.046	0.293	-4.524^{**}
	$p = 0.708$	$p = 0.403$	$p = 0.583$	$p = 0.021$
RatingBB	0.424	3.207^{*}	-0.074	-0.389
	$p = 0.792$	$p = 0.089$	$p = 0.849$	$p = 0.757$
RatingBB-	0.976	4.217^{***}	0.325	-0.260
	$p = 0.430$	$p = 0.008$	$p = 0.280$	$p = 0.785$
RatingBBB	0.580	4.158^{**}	-0.180	-0.568
	$p = 0.691$	$p = 0.022$	$p = 0.608$	$p = 0.618$
RatingBBB-	3.740	7.410^{**}	0.373	-7.099^{***}
	$p = 0.212$	$p = 0.036$	$p = 0.593$	$p = 0.009$
RatingBBB+	1.479	3.083^{**}	-0.069	-1.194
	$p = 0.271$	$p = 0.050$	$p = 0.828$	$p = 0.256$
StockWave1	0.048	0.226	0.042	0.697
	$p = 0.946$	$p = 0.771$	$p = 0.806$	$p = 0.224$
PayTypeCash and Stock	0.813	1.136^{**}	-0.077	-0.074
	$p = 0.108$	$p = 0.048$	$p = 0.507$	$p = 0.843$
PayTypeCash or Stock	0.296	0.641	0.014	-0.022
	$p = 0.474$	$p = 0.170$	$p = 0.890$	$p = 0.946$
PayTypeStock	0.991^{**}	1.157^{**}	0.004	-0.301
	$p = 0.019$	$p = 0.014$	$p = 0.961$	$p = 0.306$
BidUnsolicited	0.074	2.262^{*}	0.200	1.933^{**}
	$p = 0.946$	$p = 0.076$	$p = 0.449$	$p = 0.039$
CountDist(0.889,1.78]	1.175	0.950	0.472	-3.689^{**}
	$p = 0.545$	$p = 0.654$	$p = 0.320$	$p = 0.029$
CountDist(1.78,2.67]	1.482	1.574	0.455	-4.434^{**}
	$p = 0.471$	$p = 0.484$	$p = 0.361$	$p = 0.016$
CountDist(2.67,3.56]	3.692^{*}	1.459	0.422	-5.214^{***}
	$p = 0.071$	$p = 0.485$	$p = 0.362$	$p = 0.004$
CountDist(5.33,6.22]	1.865	1.615	0.346	-4.282^{***}
	$p = 0.310$	$p = 0.417$	$p = 0.429$	$p = 0.010$
CountDist(6.22,7.11]	0.157	-1.617	0.223	-5.130^{***}
	$p = 0.940$	$p = 0.480$	$p = 0.654$	$p = 0.008$
CountDist(7.11,8.01]				
Speed(34.7,66.4]	-0.765	-2.271^{*}	0.054	0.220
	$p = 0.449$	$p = 0.057$	$p = 0.822$	$p = 0.779$
Speed(66.4,98.1]	-1.152	-2.386^{*}	0.114	-0.011
	$p = 0.275$	$p = 0.053$	$p = 0.645$	$p = 0.990$
Speed(98.1,130]	-0.749	-3.298^{**}	0.069	-0.271
	$p = 0.535$	$p = 0.026$	$p = 0.812$	$p = 0.772$
Speed(130,162]	-0.350	-3.379^{**}	0.151	-0.653
	$p = 0.785$	$p = 0.031$	$p = 0.626$	$p = 0.517$

Speed(162,193]	−1.221	−3.604**	0.116	0.015
	$p = 0.311$	$p = 0.016$	$p = 0.684$	$p = 0.987$
Speed(193,225]	−1.181	−3.938**	0.025	0.490
	$p = 0.364$	$p = 0.015$	$p = 0.935$	$p = 0.625$
Speed(225,257]	−1.531	−4.055**	0.059	−0.855
	$p = 0.315$	$p = 0.028$	$p = 0.869$	$p = 0.468$
Speed(257,288]	−1.483	−3.625**	0.127	0.028
	$p = 0.221$	$p = 0.015$	$p = 0.654$	$p = 0.976$
Speed(288,320]	−1.155	−5.033***	0.210	−0.077
	$p = 0.390$	$p = 0.005$	$p = 0.512$	$p = 0.941$
RelatSize(7.06,14]	−0.403	1.348**	−0.023	0.429
	$p = 0.480$	$p = 0.047$	$p = 0.865$	$p = 0.340$
RelatSize(21,28]	−0.241	0.001	0.021	0.635*
	$p = 0.566$	$p = 0.998$	$p = 0.832$	$p = 0.071$
RelatSize(28,35]	0.285	−0.293	−0.038	−0.185
	$p = 0.484$	$p = 0.510$	$p = 0.694$	$p = 0.560$
RelatSize(35,42]	−0.277	0.546	0.006	0.709
	$p = 0.657$	$p = 0.430$	$p = 0.970$	$p = 0.164$
RelatSize(42,49]	−1.718	−3.340**	0.227	0.419
	$p = 0.238$	$p = 0.049$	$p = 0.508$	$p = 0.704$
RelatSize(49,56]	2.071*	0.671	0.304	−1.997**
	$p = 0.056$	$p = 0.540$	$p = 0.219$	$p = 0.024$
RelatSize(62.9,70]	4.153	7.645**	0.409	−7.490***
	$p = 0.185$	$p = 0.037$	$p = 0.575$	$p = 0.008$
DebtToVal(2.43,6.49]	−0.541	−0.309	0.032	−0.851
	$p = 0.442$	$p = 0.686$	$p = 0.847$	$p = 0.136$
DebtToVal(6.49,10.6]	3.323*	6.287***	0.327	−2.455*
	$p = 0.052$	$p = 0.004$	$p = 0.391$	$p = 0.063$
DebtToVal(10.6,14.6]				
DebtToVal(14.6,18.7]	1.053	1.209	0.295	−0.282
	$p = 0.330$	$p = 0.309$	$p = 0.260$	$p = 0.734$
DebtToVal(26.8,30.9]	1.023	1.086	0.279	−2.957**
	$p = 0.449$	$p = 0.463$	$p = 0.393$	$p = 0.015$
DebtToVal(34.9,39]	−3.906	−4.294	−0.678	6.154***
	$p = 0.133$	$p = 0.132$	$p = 0.266$	$p = 0.008$
Constant	0.667	−0.120	−0.144	8.120***
	$p = 0.784$	$p = 0.964$	$p = 0.805$	$p = 0.002$
Observations	65	65	65	65
R^2	0.912	0.912	0.757	0.888
Adjusted R^2	0.487	0.486	-0.413	0.349
Residual Std. Error (df = 11)	0.400	0.438	0.096	0.312
F Statistic (df = 53; 11)	2.147*	2.141*	0.647	1.647

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix 19: Complete regression (*Data 2 – US*)

	Dependent variable:			
	ROADiff	ROAMean	Short	Long
	(1)	(2)	(3)	(4)
DiffDebtToAsset	−0.014	−0.010	0.008^{**}	0.014
	$p = 0.187$	$p = 0.426$	$p = 0.022$	$p = 0.122$
AltZ	−0.032	−0.035	0.006	−0.012
	$p = 0.355$	$p = 0.400$	$p = 0.534$	$p = 0.675$
DebtToVal	0.165	0.133	−0.059	-0.312^{*}
	$p = 0.240$	$p = 0.428$	$p = 0.155$	$p = 0.011$
PER	−0.114	−0.107	−0.024	−0.019
	$p = 0.353$	$p = 0.469$	$p = 0.509$	$p = 0.856$
PtoB	−0.109	−0.168	-0.061^{**}	-0.139^{*}
	$p = 0.240$	$p = 0.136$	$p = 0.029$	$p = 0.079$
DtoE	0.004	−0.006	0.011^{**}	−0.009
	$p = 0.822$	$p = 0.752$	$p = 0.024$	$p = 0.484$
SameCount1	−1.222	-3.550^{***}	0.075	-1.458^{*}
	$p = 0.105$	$p = 0.0003$	$p = 0.732$	$p = 0.025$
SameSec1	−0.077	0.004	-0.138^{**}	−0.074
	$p = 0.738$	$p = 0.990$	$p = 0.045$	$p = 0.704$
Const1	0.183	0.114	−0.099	−0.117
	$p = 0.412$	$p = 0.672$	$p = 0.134$	$p = 0.537$
SecCons1	−0.343	−0.236	0.088	0.341
	$p = 0.219$	$p = 0.481$	$p = 0.285$	$p = 0.150$
RatingA+	-2.031^{*}	-4.627^{***}	0.456	-2.189^{*}
	$p = 0.051$	$p = 0.0005$	$p = 0.133$	$p = 0.015$
RatingAA	−0.752	−1.005	0.302	0.631
	$p = 0.264$	$p = 0.217$	$p = 0.130$	$p = 0.270$
RatingAA+	−0.846	−0.994	0.145	−0.021
	$p = 0.177$	$p = 0.189$	$p = 0.429$	$p = 0.969$
RatingAAA	−0.232	−0.530	0.224	−0.130
	$p = 0.638$	$p = 0.375$	$p = 0.128$	$p = 0.755$
RatingBB	−1.408	-3.386^{***}	0.119	−1.259
	$p = 0.162$	$p = 0.007$	$p = 0.686$	$p = 0.141$
RatingBB-	−1.521	-4.312^{***}	−0.200	−1.352
	$p = 0.152$	$p = 0.002$	$p = 0.517$	$p = 0.133$
StockWave1	−0.174	−0.177	-0.146^{**}	0.245
	$p = 0.362$	$p = 0.441$	$p = 0.012$	$p = 0.132$
PayTypeCash and Stock	-0.390^{**}	−0.334	0.008	−0.188
	$p = 0.041$	$p = 0.142$	$p = 0.888$	$p = 0.236$
PayTypeCash or Stock	0.166	0.171	−0.022	−0.168
	$p = 0.457$	$p = 0.526$	$p = 0.742$	$p = 0.375$
PayTypeStock	0.181	0.279	0.015	−0.318
	$p = 0.443$	$p = 0.328$	$p = 0.825$	$p = 0.117$
BidHostile	−0.311	−0.260	−0.090	0.294
	$p = 0.439$	$p = 0.591$	$p = 0.446$	$p = 0.389$
BidHostile to Friendly	0.882	0.917	0.128	0.485
	$p = 0.154$	$p = 0.218$	$p = 0.479$	$p = 0.352$
CountDist(0.812,1.62]	−1.123	-3.482^{***}	0.049	-1.778^{***}
	$p = 0.155$	$p = 0.001$	$p = 0.833$	$p = 0.010$
CountDist(1.62,2.44]	-1.399^{*}	-3.908^{***}	0.064	-1.388^{**}
	$p = 0.078$	$p = 0.0002$	$p = 0.780$	$p = 0.040$

CountDist(3.25,4.06]	-1.342	-4.141^{***}	0.129	-1.404^{*}
	$p = 0.133$	$p = 0.0004$	$p = 0.620$	$p = 0.066$
CountDist(4.87,5.68]	-2.451^{***}	-4.198^{***}	-0.214	-1.914^{***}
	$p = 0.005$	$p = 0.0002$	$p = 0.385$	$p = 0.010$
CountDist(5.68,6.5]				
CountDist(6.5,7.32]				
Speed(43.3,75.6]	0.166	0.306	-0.040	-0.214
	$p = 0.487$	$p = 0.291$	$p = 0.569$	$p = 0.294$
Speed(75.6,108]	0.267	0.449	-0.063	-0.166
	$p = 0.290$	$p = 0.143$	$p = 0.399$	$p = 0.437$
Speed(108,140]	-0.058	0.204	-0.035	-0.013
	$p = 0.852$	$p = 0.588$	$p = 0.706$	$p = 0.960$
Speed(140,172]	0.215	0.306	-0.019	0.004
	$p = 0.491$	$p = 0.416$	$p = 0.838$	$p = 0.988$
Speed(172,205]	0.352	0.522	-0.050	0.025
	$p = 0.263$	$p = 0.170$	$p = 0.590$	$p = 0.925$
Speed(205,237]	-0.173	-0.502	-0.101	0.151
	$p = 0.634$	$p = 0.254$	$p = 0.348$	$p = 0.623$
Speed(237,269]	0.457	0.603	-0.054	0.022
	$p = 0.188$	$p = 0.151$	$p = 0.593$	$p = 0.941$
Speed(269,302]	-1.020^{**}	-0.607	0.062	0.446
	$p = 0.030$	$p = 0.274$	$p = 0.646$	$p = 0.253$
Speed(302,334]	-0.355	-0.252	-0.027	0.073
	$p = 0.310$	$p = 0.550$	$p = 0.789$	$p = 0.805$
RelatSize(5.9,11.8]	0.203	0.327^{*}	0.051	-0.084
	$p = 0.140$	$p = 0.051$	$p = 0.206$	$p = 0.465$
RelatSize(11.8,17.7]	-0.300	-0.137	0.072	-0.044
	$p = 0.285$	$p = 0.683$	$p = 0.383$	$p = 0.854$
RelatSize(17.7,23.6]	-0.198	-0.323	0.0004	-0.162
	$p = 0.329$	$p = 0.190$	$p = 0.995$	$p = 0.345$
RelatSize(23.6,29.5]	-0.386	0.108	0.061	0.364
	$p = 0.340$	$p = 0.824$	$p = 0.607$	$p = 0.289$

RelatSize(29.5,35.4]	−0.587	−0.569	−0.009	0.268
	$p = 0.396$	$p = 0.495$	$p = 0.967$	$p = 0.647$
RelatSize(35.4,41.3]	−0.254	−0.203	0.038	−0.877
	$p = 0.690$	$p = 0.792$	$p = 0.841$	$p = 0.109$
RelatSize(41.3,47.2]	0.092	0.168	0.048	0.211
	$p = 0.768$	$p = 0.656$	$p = 0.602$	$p = 0.429$
RelatSize(47.2,53.1]	−3.141***	−3.026***	0.016	0.395
	$p = 0.00000$	$p = 0.00001$	$p = 0.913$	$p = 0.354$
RelatSize(53.1,59]	−0.180	0.143	0.110	−0.263
	$p = 0.712$	$p = 0.808$	$p = 0.445$	$p = 0.525$
FCFMarg(-5.55,-2.9]	−0.627	−0.991	0.040	−0.144
	$p = 0.229$	$p = 0.117$	$p = 0.793$	$p = 0.742$
FCFMarg(-2.9,-0.25]	−0.358	−0.286	0.046	−0.492
	$p = 0.368$	$p = 0.550$	$p = 0.692$	$p = 0.148$
FCFMarg(-0.25,2.4]	−0.294	−0.600	0.026	−0.059
	$p = 0.434$	$p = 0.189$	$p = 0.817$	$p = 0.853$
FCFMarg(2.4,5.05]	−0.390	−0.665	0.010	0.054
	$p = 0.280$	$p = 0.129$	$p = 0.922$	$p = 0.859$
FCFMarg(5.05,7.71]	0.031	−0.005	0.090	−0.051
	$p = 0.937$	$p = 0.992$	$p = 0.425$	$p = 0.875$
FCFMarg(7.71,10.4]	−0.820**	−0.802*	0.055	0.146
	$p = 0.041$	$p = 0.095$	$p = 0.636$	$p = 0.660$
FCFMarg(10.4,13]	0.303	−0.027	0.140	0.057
	$p = 0.476$	$p = 0.959$	$p = 0.267$	$p = 0.874$
FCFMarg(13,15.7]	−0.066	−0.275	−0.197	0.061
	$p = 0.887$	$p = 0.624$	$p = 0.154$	$p = 0.878$
FCFMarg(15.7,18.3]	−0.234	−0.984*	0.027	0.023
	$p = 0.604$	$p = 0.075$	$p = 0.839$	$p = 0.953$
CashR(0.147,0.29]	−0.172	−0.217	0.072	−0.045
	$p = 0.393$	$p = 0.372$	$p = 0.229$	$p = 0.793$
CashR(0.29,0.433]	0.284*	0.269	−0.047	−0.134
	$p = 0.080$	$p = 0.167$	$p = 0.317$	$p = 0.325$
CashR(0.433,0.576]	0.254	0.360*	−0.010	−0.031
	$p = 0.134$	$p = 0.080$	$p = 0.847$	$p = 0.825$
CashR(0.576,0.72]	0.200	0.360	0.086	−0.003
	$p = 0.361$	$p = 0.177$	$p = 0.186$	$p = 0.988$
CashR(0.72,0.863]	0.119	0.096	0.042	−0.148
	$p = 0.614$	$p = 0.736$	$p = 0.544$	$p = 0.460$
CashR(0.863,1.01]	0.610	0.073	0.070	0.034
	$p = 0.232$	$p = 0.906$	$p = 0.641$	$p = 0.937$
CashR(1.01,1.15]	−0.984**	−2.694***	0.113	−1.511***
	$p = 0.041$	$p = 0.00002$	$p = 0.416$	$p = 0.0005$
CashR(1.15,1.29]				
CashR(1.29,1.44]	0.909**	0.364	0.190*	0.371
	$p = 0.020$	$p = 0.427$	$p = 0.093$	$p = 0.251$
Constant	4.706***	7.253***	0.497	3.502***
	$p = 0.00004$	$p = 0.00000$	$p = 0.108$	$p = 0.0003$
Observations	107	107	107	107
R^2	0.780	0.730	0.734	0.672
Adjusted R^2	0.482	0.363	0.373	0.227
Residual Std. Error (df = 45)	0.390	0.471	0.115	0.331
F Statistic (df = 61; 45)	2.614***	1.990***	2.033***	1.512*

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix 20: Stepwise regression (*Data 1 – Global*)

	Dependent variable:			
	ROADiff	ROAMean	Short	Long
	(1)	(2)	(3)	(4)
PER	0.149	0.109		−0.224*
	$p = 0.264$	$p = 0.438$		$p = 0.064$
PtoB	−0.251	−0.126	0.029	−0.119
	$p = 0.155$	$p = 0.355$	$p = 0.320$	$p = 0.440$
CashR	−0.251*			0.196
	$p = 0.055$			$p = 0.137$
DtoE	−0.078		−0.019**	0.027
	$p = 0.113$		$p = 0.022$	$p = 0.529$
AltZ	0.664**	0.246		−0.377
	$p = 0.024$	$p = 0.273$		$p = 0.119$
FCFMarg	−0.024	−0.046**		0.030*
	$p = 0.210$	$p = 0.032$		$p = 0.075$
DiffDebtToAsset			−0.005	
			$p = 0.259$	
SameSec1	−1.258***	−0.609**	−0.079	0.235
	$p = 0.0005$	$p = 0.049$	$p = 0.235$	$p = 0.357$
Const1	−0.366	−0.958**	−0.225**	−0.378
	$p = 0.382$	$p = 0.038$	$p = 0.045$	$p = 0.319$
SecCons1	0.317	0.998*	0.195	0.740*
	$p = 0.480$	$p = 0.055$	$p = 0.125$	$p = 0.081$
RatingA-	0.668	2.825**	−0.182	−1.246
	$p = 0.547$	$p = 0.011$	$p = 0.352$	$p = 0.205$
RatingAA	0.663	2.949**	−0.110	−0.818
	$p = 0.563$	$p = 0.016$	$p = 0.562$	$p = 0.408$
RatingAA-	1.062	3.577***	−0.072	−1.697
	$p = 0.398$	$p = 0.009$	$p = 0.747$	$p = 0.137$
RatingAA+	0.926	3.497***	−0.085	−1.244
	$p = 0.351$	$p = 0.004$	$p = 0.664$	$p = 0.171$
RatingAAA	0.661	3.177***	−0.199	−1.142
	$p = 0.532$	$p = 0.007$	$p = 0.317$	$p = 0.235$
RatingB	0.917	2.138	0.175	−4.382**
	$p = 0.590$	$p = 0.202$	$p = 0.602$	$p = 0.017$
RatingBB	0.421	2.683**	−0.157	−0.359
	$p = 0.756$	$p = 0.035$	$p = 0.527$	$p = 0.766$
RatingBB-	0.997	4.385***	0.301	−0.271
	$p = 0.358$	$p = 0.002$	$p = 0.161$	$p = 0.768$
RatingBBB	0.564	3.748***	−0.215	−0.518
	$p = 0.658$	$p = 0.003$	$p = 0.326$	$p = 0.634$
RatingBBB-	3.818*	7.094***	0.207	−6.736***
	$p = 0.069$	$p = 0.005$	$p = 0.610$	$p = 0.005$
RatingBBB+	1.475	2.795**	−0.089	−1.070
	$p = 0.182$	$p = 0.018$	$p = 0.670$	$p = 0.262$
StockWave1				0.594
				$p = 0.215$
PayTypeCash and Stock	0.808*	1.044**	−0.077	−0.048
	$p = 0.066$	$p = 0.021$	$p = 0.408$	$p = 0.891$
PayTypeCash or Stock	0.263	0.553*	0.029	0.018
	$p = 0.394$	$p = 0.080$	$p = 0.602$	$p = 0.950$
PayTypeStock	0.997***	1.136***	0.006	−0.283
	$p = 0.006$	$p = 0.003$	$p = 0.921$	$p = 0.309$
BidUnsolicited		2.446***	0.255	1.795**
		$p = 0.006$	$p = 0.151$	$p = 0.028$
CountDist(0.889,1.78]	−0.503	−0.159	0.056	0.798**
	$p = 0.235$	$p = 0.717$	$p = 0.531$	$p = 0.044$
CountDist(1.78,2.67]	−0.174	0.514*	0.035	0.079
	$p = 0.480$	$p = 0.065$	$p = 0.520$	$p = 0.748$
CountDist(2.67,3.56]	2.017***	0.301	0.002	−0.752
	$p = 0.005$	$p = 0.641$	$p = 0.987$	$p = 0.172$
CountDist(5.33,6.22]	0.182	0.374	−0.082	0.228
	$p = 0.593$	$p = 0.166$	$p = 0.187$	$p = 0.441$
CountDist(6.22,7.11]	−1.482***	−2.861***	−0.232**	−0.630
	$p = 0.003$	$p = 0.00002$	$p = 0.038$	$p = 0.164$
CountDist(7.11,8.01]	−1.771	−1.392	−0.348	4.374***
	$p = 0.250$	$p = 0.265$	$p = 0.262$	$p = 0.010$

Speed(34.7,66.4]	−0.715	−2.018**	0.039	0.154
	$p = 0.399$	$p = 0.016$	$p = 0.779$	$p = 0.833$
Speed(66.4,98.1]	−1.109	−2.143**	0.100	−0.032
	$p = 0.221$	$p = 0.013$	$p = 0.516$	$p = 0.967$
Speed(98.1,130]	−0.685	−2.912***	0.063	−0.329
	$p = 0.503$	$p = 0.003$	$p = 0.723$	$p = 0.712$
Speed(130,162]	−0.265	−3.019***	0.120	−0.709
	$p = 0.799$	$p = 0.002$	$p = 0.494$	$p = 0.460$
Speed(162,193]	−1.166	−3.248***	0.107	−0.068
	$p = 0.252$	$p = 0.002$	$p = 0.551$	$p = 0.937$
Speed(193,225]	−1.127	−3.594***	0.018	0.379
	$p = 0.300$	$p = 0.002$	$p = 0.919$	$p = 0.680$
Speed(225,257]	−1.453	−3.688***	0.044	−0.886
	$p = 0.254$	$p = 0.003$	$p = 0.828$	$p = 0.433$
Speed(257,288]	−1.418	−3.269***	0.115	−0.065
	$p = 0.160$	$p = 0.002$	$p = 0.524$	$p = 0.940$
Speed(288,320]	−1.088	−4.684***	0.197	−0.125
	$p = 0.340$	$p = 0.0002$	$p = 0.318$	$p = 0.899$
RelatSize(7.06,14]	−0.401	1.282**	−0.036	0.430
	$p = 0.411$	$p = 0.026$	$p = 0.734$	$p = 0.320$
RelatSize(21,28]	−0.243	0.027	0.037	0.640*
	$p = 0.512$	$p = 0.944$	$p = 0.608$	$p = 0.058$
RelatSize(28,35]	0.301	−0.305	−0.040	−0.209
	$p = 0.387$	$p = 0.377$	$p = 0.609$	$p = 0.484$
RelatSize(35,42]	−0.276	0.563	0.023	0.713
	$p = 0.617$	$p = 0.335$	$p = 0.838$	$p = 0.146$
RelatSize(42,49]	−1.642	−2.863***	0.232	0.260
	$p = 0.164$	$p = 0.010$	$p = 0.228$	$p = 0.791$
RelatSize(49,56]	2.083**	0.761	0.283*	−1.868**
	$p = 0.013$	$p = 0.238$	$p = 0.088$	$p = 0.015$
RelatSize(62.9,70]	4.268*	7.381***	0.229	−7.174***
	$p = 0.058$	$p = 0.006$	$p = 0.588$	$p = 0.005$
DebtToVal(2.43,6.49]	−0.519	−0.376	0.005	−0.739
	$p = 0.151$	$p = 0.399$	$p = 0.961$	$p = 0.108$
DebtToVal(6.49,10.6]	3.297**	6.043***	0.282	−2.225**
	$p = 0.013$	$p = 0.0002$	$p = 0.234$	$p = 0.044$
DebtToVal(10.6,14.6]				
DebtToVal(14.6,18.7]	1.048	1.398*	0.300*	−0.208
	$p = 0.256$	$p = 0.065$	$p = 0.090$	$p = 0.788$
DebtToVal(26.8,30.9]	1.064	0.936	0.187	−2.782***
	$p = 0.217$	$p = 0.254$	$p = 0.269$	$p = 0.009$
DebtToVal(34.9,39]	−4.031**	−4.496**	−0.552	5.964***
	$p = 0.040$	$p = 0.017$	$p = 0.155$	$p = 0.006$
Constant	2.339**	1.492*	0.349**	3.515***
	$p = 0.028$	$p = 0.070$	$p = 0.037$	$p = 0.002$
Observations	65	65	65	65
R^2	0.912	0.908	0.750	0.887
Adjusted R^2	0.596	0.607	0.001	0.395
Residual Std. Error	0.355 (df = 14)	0.382 (df = 15)	0.081 (df = 16)	0.301 (df = 12)
F Statistic	2.885** (df = 50; 14)	3.019** (df = 49; 15)	1.001 (df = 48; 16)	1.803 (df = 52; 12)
Note:				*p<0.1; **p<0.05; ***p<0.01

Appendix 21: Stepwise regression (*Data 2 – US*)

	Dependent variable:			
	ROADiff	ROAMean	Short	Long
	(1)	(2)	(3)	(4)
DiffDebtToAsset	-0.017^{*}		0.007^{***}	0.015^{**}
	$p = 0.099$		$p = 0.004$	$p = 0.033$
AltZ	-0.038	-0.034	0.009	
	$p = 0.229$	$p = 0.317$	$p = 0.225$	
DebtToVal	0.178		-0.067^{**}	-0.303^{***}
	$p = 0.185$		$p = 0.018$	$p = 0.002$
PER	-0.122			
	$p = 0.303$			
PtoB	-0.113	-0.168^{*}	-0.051^{**}	-0.121^{*}
	$p = 0.203$	$p = 0.094$	$p = 0.016$	$p = 0.065$
DtoE			0.010^{***}	
			$p = 0.008$	
SameSec1			-0.138^{***}	
			$p = 0.008$	
Const1	0.235		-0.088^{*}	
	$p = 0.105$		$p = 0.082$	
SecCons1	-0.412^{**}		0.078	0.201^{**}
	$p = 0.017$		$p = 0.206$	$p = 0.031$
RatingA+	-0.925	-0.760	0.406^{***}	-0.656
	$p = 0.176$	$p = 0.309$	$p = 0.009$	$p = 0.180$
RatingAA	-0.744	-0.830	0.364^{**}	0.431
	$p = 0.253$	$p = 0.255$	$p = 0.017$	$p = 0.362$
RatingAA+	-0.814	-0.919	0.175	-0.073
	$p = 0.164$	$p = 0.143$	$p = 0.164$	$p = 0.852$
RatingAAA	-0.234	-0.325	0.277^{***}	-0.233
	$p = 0.622$	$p = 0.537$	$p = 0.008$	$p = 0.515$
RatingBB	-1.402	-3.159^{***}	0.200	-1.219
	$p = 0.154$	$p = 0.005$	$p = 0.379$	$p = 0.103$
RatingBB-	-0.354	-0.372	-0.214	0.017
	$p = 0.597$	$p = 0.608$	$p = 0.150$	$p = 0.972$
StockWave1		-0.245	-0.155^{***}	
		$p = 0.231$	$p = 0.0002$	
PayTypeCash and Stock	-0.459^{***}	-0.281		
	$p = 0.008$	$p = 0.129$		
PayTypeCash or Stock	0.122	0.238		
	$p = 0.566$	$p = 0.320$		
PayTypeStock	0.093	0.289		
	$p = 0.658$	$p = 0.207$		
BidHostile	-0.312			0.306
	$p = 0.422$			$p = 0.287$
BidHostile to Friendly	0.971			0.446
	$p = 0.102$			$p = 0.276$
CountDist(0.812,1.62]	0.061	0.356	-0.030	-0.269
	$p = 0.842$	$p = 0.197$	$p = 0.560$	$p = 0.224$
CountDist(1.62,2.44]	-0.180	-0.270	-0.020	0.058
	$p = 0.368$	$p = 0.214$	$p = 0.651$	$p = 0.687$
CountDist(3.25,4.06]	-0.160	-0.384	0.149	0.192
	$p = 0.759$	$p = 0.493$	$p = 0.142$	$p = 0.585$
CountDist(4.87,5.68]	-1.230^{***}	-0.655	-0.281^{***}	-0.314
	$p = 0.002$	$p = 0.106$	$p = 0.002$	$p = 0.226$
CountDist(5.68,6.5]	1.242^{*}	3.734^{***}	-0.151	1.704^{***}
	$p = 0.072$	$p = 0.00001$	$p = 0.374$	$p = 0.002$
CountDist(6.5,7.32]				
Speed(43.3,75.6]	0.176	0.278		
	$p = 0.442$	$p = 0.276$		
Speed(75.6,108]	0.290	0.376		
	$p = 0.230$	$p = 0.148$		
Speed(108,140]	-0.003	0.214		
	$p = 0.992$	$p = 0.495$		
Speed(140,172]	0.305	0.159		
	$p = 0.290$	$p = 0.619$		
Speed(172,205]	0.424	0.481		
	$p = 0.155$	$p = 0.137$		
Speed(205,237]	-0.106	-0.589		

Speed(237,269]	0.521	0.502		
	$p = 0.114$	$p = 0.154$		
Speed(269,302]	-0.935^{**}	-0.646		
	$p = 0.037$	$p = 0.166$		
Speed(302,334]	-0.302	-0.413		
	$p = 0.366$	$p = 0.239$		
RelatSize(5.9,11.8]	0.200	0.331^{**}		-0.051
	$p = 0.132$	$p = 0.032$		$p = 0.544$
RelatSize(11.8,17.7]	-0.308	0.019		-0.014
	$p = 0.252$	$p = 0.947$		$p = 0.937$
RelatSize(17.7,23.6]	-0.164	-0.337		-0.234^{*}
	$p = 0.399$	$p = 0.113$		$p = 0.081$
RelatSize(23.6,29.5]	-0.421	0.163		0.287
	$p = 0.279$	$p = 0.681$		$p = 0.297$
RelatSize(29.5,35.4]	-0.472	-0.264		-0.010
	$p = 0.464$	$p = 0.692$		$p = 0.982$
RelatSize(35.4,41.3]	-0.317	0.034		-0.825^{*}
	$p = 0.609$	$p = 0.956$		$p = 0.053$
RelatSize(41.3,47.2]	0.109	0.024		0.213
	$p = 0.719$	$p = 0.940$		$p = 0.336$
RelatSize(47.2,53.1]	-3.162^{***}	-2.784^{***}		0.434
	$p = 0.00000$	$p = 0.00001$		$p = 0.211$
RelatSize(53.1,59]	-0.202	0.058		-0.188
	$p = 0.666$	$p = 0.907$		$p = 0.571$
FCFMarg(-5.55,-2.9]	-0.664	-0.986^{*}	0.008	-0.108
	$p = 0.191$	$p = 0.068$	$p = 0.933$	$p = 0.772$
FCFMarg(-2.9,-0.25]	-0.427	-0.182	0.074	-0.465
	$p = 0.257$	$p = 0.663$	$p = 0.349$	$p = 0.107$
FCFMarg(-0.25,2.4]	-0.340	-0.434	0.063	-0.058
	$p = 0.348$	$p = 0.282$	$p = 0.368$	$p = 0.831$
FCFMarg(2.4,5.05]	-0.403	-0.593	0.033	0.040
	$p = 0.252$	$p = 0.138$	$p = 0.620$	$p = 0.877$
FCFMarg(5.05,7.71]	-0.021	0.061	0.109	0.004
	$p = 0.955$	$p = 0.883$	$p = 0.134$	$p = 0.990$
FCFMarg(7.71,10.4]	-0.894^{**}	-0.568	0.077	0.213
	$p = 0.019$	$p = 0.170$	$p = 0.304$	$p = 0.448$
FCFMarg(10.4,13]	0.227	0.035	0.164^{*}	0.129
	$p = 0.574$	$p = 0.940$	$p = 0.053$	$p = 0.664$
FCFMarg(13,15.7]	-0.038	-0.276	-0.173^{*}	-0.033
	$p = 0.932$	$p = 0.577$	$p = 0.059$	$p = 0.921$
FCFMarg(15.7,18.3]	-0.212	-0.986^{*}	0.045	-0.119
	$p = 0.629$	$p = 0.052$	$p = 0.614$	$p = 0.704$
CashR(0.147,0.29]	-0.191	-0.156	0.069^{*}	0.040
	$p = 0.290$	$p = 0.430$	$p = 0.089$	$p = 0.754$
CashR(0.29,0.433]	0.304^{**}	0.223	-0.069^{*}	-0.099
	$p = 0.048$	$p = 0.189$	$p = 0.058$	$p = 0.375$
CashR(0.433,0.576]	0.261^{*}	0.356^{**}	-0.025	0.039
	$p = 0.094$	$p = 0.041$	$p = 0.510$	$p = 0.734$
CashR(0.576,0.72]	0.201	0.305	0.032	0.023
	$p = 0.333$	$p = 0.155$	$p = 0.480$	$p = 0.877$
CashR(0.72,0.863]	0.125	0.123	0.014	-0.057
	$p = 0.571$	$p = 0.620$	$p = 0.776$	$p = 0.691$
CashR(0.863,1.01]	0.700	-0.182	0.051	-0.176
	$p = 0.151$	$p = 0.739$	$p = 0.649$	$p = 0.610$
CashR(1.01,1.15]	-1.014^{**}	-2.703^{***}	0.121	-1.480^{***}
	$p = 0.021$	$p = 0.00000$	$p = 0.285$	$p = 0.00004$
CashR(1.15,1.29]			0.005	
			$p = 0.967$	
CashR(1.29,1.44]	0.943^{**}	0.321	0.190^{**}	0.296
	$p = 0.012$	$p = 0.431$	$p = 0.033$	$p = 0.271$
Constant	3.524^{***}	3.074^{***}	0.415^{***}	1.653^{***}
	$p = 0.00004$	$p = 0.0001$	$p = 0.003$	$p = 0.001$
Observations	107	107	107	107
R^2	0.776	0.708	0.690	0.595
Adjusted R^2	0.504	0.426	0.517	0.319
Residual Std. Error	0.382 (df = 48)	0.447 (df = 54)	0.101 (df = 68)	0.311 (df = 63)
F Statistic	2.861^{***} (df = 58; 48)	2.516^{***} (df = 52; 54)	3.987^{***} (df = 38; 68)	2.153^{***} (df = 43; 63)

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix 22: Code from R Studio

```
##########################################################################
#####
############################DATA
IMPORT##########################################
##########################################################################
#####

glo = read_csv("C:/Users/boris/Desktop/Global.csv")
#View(glo)
spec(glo)
us = read_csv("C:/Users/boris/Desktop/US.csv")
#View(us)
spec(us)

summary(glo)
summary(us)

##########################################################################
#####
############################NUM
VAR################################################
##########################################################################
#####

glo_count = as.data.frame(cut(glo$CountDist, 9, include.lowest = TRUE))
names(glo_count) = "CountDist"
us_count = as.data.frame(cut(us$CountDist, 9, include.lowest = TRUE))
names(us_count) = "CountDist"

glo_num = data.frame(glo$DiffDebtToAsset, glo$RelatSize, glo$PER,
                     glo$PtoB, glo$Speed, glo$FCFMarg, glo$CashR, glo$DtoE,
                     glo$AltZ, glo$DebtToVal,glo$ROADiff, glo$ROAMean,
                     glo$Short, glo$Long)
summary(glo_num)

us_num = data.frame(us$DiffDebtToAsset, us$RelatSize, us$PER,
                     us$PtoB, us$Speed, us$FCFMarg, us$CashR, us$DtoE,
                     us$AltZ, us$DebtToVal, us$ROADiff, us$ROAMean,
                     us$Short, us$Long)
summary(us_num)

glo_var = format(apply(glo_num, 2,var), scientific = FALSE)
glo_var
us_var = format(apply(us_num, 2,var), scientific = FALSE)
us_var
glo_skew = format(apply(glo_num, 2, e1071::skewness), scientific = FALSE)
glo_skew
us_skew = format(apply(us_num, 2, e1071::skewness), scientific = FALSE)
us_skew
glo_kurt = format(apply(glo_num, 2, e1071::kurtosis), scientific = FALSE)
glo_kurt
us_kurt = format(apply(us_num, 2, e1071::kurtosis), scientific = FALSE)
us_kurt

#create_report(glo_num)
#create_report(us_num)

##########################################################################
#####
```

```
############################DATA
TRANSFO#########################################
###########################################################################
#####

apply(glo_num, 2, boxplot)
apply(glo_num, 2, boxplot)
outliers <- function(x) {
  Q1 <- quantile(x, probs=.25)
  Q3 <- quantile(x, probs=.75)
  iqr = Q3-Q1
  upper_limit = Q3 + (iqr*1.5)
  lower_limit = Q1 - (iqr*1.5)
  x > upper_limit | x < lower_limit
}
remove_outliers = function(df, cols = names(df)) {
  for (col in cols) {
    df <- df[!outliers(df[[col]]),]
  }
  df
}

glo_temp = remove_outliers(glo_num[1:11])
summary(glo_temp)
glo_num_out = slice(glo_num, as.numeric(rownames(glo_temp)))
#create_report(glo_num_out)

us_temp = remove_outliers(us_num[1:11])
summary(us_temp)
us_num_out = slice(us_num, as.numeric(rownames(us_temp)))
#create_report(us_num_out)


p1 = ggplot(glo_num_out, aes(glo.RelatSize, glo.ROADiff) ) +
  geom_point() +
  stat_smooth() +
  theme_bw()
p2 = ggplot(glo_num_out, aes(glo.Speed, glo.ROADiff) ) +
  geom_point() +
  stat_smooth() +
  theme_bw()
p3 = ggplot(us_num_out, aes(us.RelatSize, us.ROADiff) ) +
  geom_point() +
  stat_smooth() +
  theme_bw()
p4 = ggplot(us_num_out, aes(us.Speed, us.ROADiff) ) +
  geom_point() +
  stat_smooth() +
  theme_bw()
ggarrange(p1, p2, p3, p4, ncol = 2, nrow = 2)

glo_speed = as.data.frame(cut(glo_num_out$glo.Speed, 10, include.lowest =
TRUE))
names(glo_speed) = "Speed"
glo_size = as.data.frame(cut(glo_num_out$glo.RelatSize, 10, include.lowest
= TRUE))
names(glo_size) = "RelatSize"

us_speed = as.data.frame(cut(us_num_out$us.Speed, 10, include.lowest =
TRUE))
names(us_speed) = "Speed"
```

```
us_size = as.data.frame(cut(us_num_out$us.RelatSize, 10, include.lowest =
TRUE))
names(us_size) = "RelatSize"

glo_num_out = glo_num_out[,-2]
glo_num_out = glo_num_out[,-4]
us_num_out = us_num_out[,-2]
us_num_out = us_num_out[,-4]


glo_sum = as.data.frame(apply(glo_num_out,2,summary))
us_sum = as.data.frame(apply(us_num_out,2,summary))

glo_var = as.numeric(format(apply(glo_num_out, 2,var), scientific = FALSE))
glo_sum = rbind(glo_sum, glo_var)
rownames(glo_sum)[7] = "Var"
us_var = as.numeric(format(apply(us_num_out, 2,var), scientific = FALSE))
us_sum = rbind(us_sum, us_var)
rownames(us_sum)[7] = "Var"

glo_skew = as.numeric(format(apply(glo_num_out, 2,e1071::skewness),
scientific = FALSE))
glo_sum = rbind(glo_sum, glo_skew)
rownames(glo_sum)[8] = "Skew"
us_skew = as.numeric(format(apply(us_num_out, 2,e1071::skewness),
scientific = FALSE))
us_sum = rbind(us_sum, us_skew)
rownames(us_sum)[8] = "Skew"

glo_kurt = as.numeric(format(apply(glo_num_out, 2,e1071::kurtosis),
scientific = FALSE))
glo_sum = rbind(glo_sum, glo_kurt)
rownames(glo_sum)[9] = "Kurt"
us_kurt = as.numeric(format(apply(us_num_out, 2,e1071::kurtosis),
scientific = FALSE))
us_sum = rbind(us_sum, us_kurt)
rownames(us_sum)[9] = "Kurt"

glo_sum = round(glo_sum,2)
us_sum = round(us_sum,2)

colnames(glo_sum) = sub("glo.","",colnames(glo_sum))
colnames(us_sum) = sub("us.","",colnames(us_sum))

stargazer(glo_sum, summary = FALSE)
stargazer(us_sum, summary = FALSE)

################################GLOBAL######################################
#####

format(apply(glo_num_out, 2, shapiro.test), scientific = FALSE)

glo_box = data.frame(glo_num_out$glo.PER, glo_num_out$glo.PtoB,
glo_num_out$glo.CashR,
                      glo_num_out$glo.DtoE, glo_num_out$glo.AltZ)
apply(glo_box, 2, shapiro.test)
#(mfrow=c(2,3))
apply(glo_box, 2,hist)
box_temp = preProcess(glo_box, method = "BoxCox")
glo_box = predict(box_temp, glo_box)
apply(glo_box, 2, shapiro.test)
```

```
par(mfrow=c(2,3))
apply(glo_box, 2,hist)
sapply(box_temp$bc, function(x) x$lambda)

glo_yj = as.data.frame(glo_num_out$glo.DebtToVal)
apply(glo_yj, 2, shapiro.test)
#(mfrow=c(2,3))
apply(glo_yj, 2,hist)
yj_temp = preProcess(glo_yj, method = "YeoJohnson")
glo_yj = predict(yj_temp, glo_yj)
apply(glo_yj, 2, shapiro.test)
par(mfrow=c(2,3))
apply(glo_yj, 2,hist)

glo_debttoval = as.data.frame(cut(glo_num_out$glo.DebtToVal, 10,
include.lowest = TRUE))
names(glo_debttoval) = "DebtToVal"


glo_num_fin = cbind(glo_box, glo_num_out$glo.DiffDebtToAsset,
glo_num_out$glo.FCFMarg,
                    glo_num_out$glo.ROADiff,
                    glo_num_out$glo.ROAMean, glo_num_out$glo.Short,
                    glo_num_out$glo.Long)
names(glo_num_fin)
names(glo_num_fin) = sub("glo_num_out.glo.","",names(glo_num_fin))
names(glo_num_fin)
apply(glo_num_fin, 2, shapiro.test)

r = cor(as.matrix(glo_num_fin))
corrplot(r, type = "upper", order = "hclust",
         tl.col = "black", tl.srt = 45)

##############################US######################################
#####

format(apply(us_num_out, 2, shapiro.test), scientific = FALSE)

us_box = data.frame(us_num_out$us.PER, us_num_out$us.PtoB,
us_num_out$us.CashR,
                     us_num_out$us.DtoE)
apply(us_box, 2, shapiro.test)
par(mfrow=c(2,3))
apply(us_box, 2,hist)
box_temp = preProcess(us_box, method = "BoxCox")
us_box = predict(box_temp, us_box)
apply(us_box, 2, shapiro.test)
par(mfrow=c(2,3))
apply(us_box, 2,hist)
sapply(box_temp$bc, function(x) x$lambda)

us_yj = data.frame(us_num_out$us.DebtToVal, us_num_out$us.FCFMarg)
apply(us_yj, 2, shapiro.test)
par(mfrow=c(2,3))
apply(us_yj, 2,hist)
yj_temp = preProcess(us_yj, method = "YeoJohnson")
us_yj = predict(yj_temp, us_yj)
apply(us_yj, 2, shapiro.test)
par(mfrow=c(2,3))
apply(us_yj, 2,hist)
```

```
us_fcfmarg = as.data.frame(cut(us_num_out$us.FCFMarg, 10, include.lowest =
TRUE))
names(us_fcfmarg) = "FCFMarg"
us_cashr = as.data.frame(cut(us_num_out$us.CashR, 10, include.lowest =
TRUE))
names(us_cashr) = "CashR"

us_num_fin =
cbind(data.frame(us_num_out$us.DiffDebtToAsset),us_num_out$us.AltZ,
                   us_yj, us_box, us_num_out$us.ROADiff,
                   us_num_out$us.ROAMean, us_num_out$us.Short,
                   us_num_out$us.Long)

names(us_num_fin)
names(us_num_fin) = sub("us_num_out.us.","",names(us_num_fin))
names(us_num_fin)
us_num_fin = us_num_fin[,-7]
us_num_fin = us_num_fin[,-4]

apply(us_num_fin, 2, shapiro.test)

r = cor(as.matrix(us_num_fin))
corrplot(r, type = "upper", order = "hclust",
         tl.col = "black", tl.srt = 45)

#############################################################################
#####
############################SUMMARY##########################################
#####
#############################################################################
#####

glo_sum = as.data.frame(apply(glo_num_fin,2,summary))
us_sum = as.data.frame(apply(us_num_fin,2,summary))

glo_var = as.numeric(format(apply(glo_num_fin, 2,var), scientific = FALSE))
glo_sum = rbind(glo_sum, glo_var)
rownames(glo_sum)[7] = "Var"
us_var = as.numeric(format(apply(us_num_fin, 2,var), scientific = FALSE))
us_sum = rbind(us_sum, us_var)
rownames(us_sum)[7] = "Var"

glo_skew = as.numeric(format(apply(glo_num_fin, 2,e1071::skewness),
scientific = FALSE))
glo_sum = rbind(glo_sum, glo_skew)
rownames(glo_sum)[8] = "Skew"
us_skew = as.numeric(format(apply(us_num_fin, 2,e1071::skewness),
scientific = FALSE))
us_sum = rbind(us_sum, us_skew)
rownames(us_sum)[8] = "Skew"

glo_kurt = as.numeric(format(apply(glo_num_fin, 2,e1071::kurtosis),
scientific = FALSE))
glo_sum = rbind(glo_sum, glo_kurt)
rownames(glo_sum)[9] = "Kurt"
us_kurt = as.numeric(format(apply(us_num_fin, 2,e1071::kurtosis),
scientific = FALSE))
us_sum = rbind(us_sum, us_kurt)
rownames(us_sum)[9] = "Kurt"

glo_sum = round(glo_sum,2)
```

```
us_sum = round(us_sum,2)

colnames(glo_sum) = sub("glo.","",colnames(glo_sum))
colnames(us_sum) = sub("us.","",colnames(us_sum))

stargazer(glo_sum, summary = FALSE)
stargazer(us_sum, summary = FALSE)

############################################################################
#####
############################CAT
VAR##############################################
############################################################################
#####

glo_cat = data.frame(glo$SameCount, glo$SameSec, glo$Const, glo$SecCons,
                     glo$Rating, glo$StockWave, glo$PayType, glo$Bid)
glo_cat = cbind(glo_cat, glo_count)

us_cat = data.frame(us$SameCount, us$SameSec, us$Const, us$SecCons,
                     us$Rating, us$StockWave, us$PayType, us$Bid)
us_cat = cbind(us_cat, us_count)

glo_cat_out = as.data.frame(slice(glo_cat, as.numeric(rownames(glo_temp))))
glo_cat_out$glo.SameCount = as.factor(glo_cat_out$glo.SameCount)
glo_cat_out$glo.SameSec = as.factor(glo_cat_out$glo.SameSec)
glo_cat_out$glo.Const = as.factor(glo_cat_out$glo.Const)
glo_cat_out$glo.SecCons = as.factor(glo_cat_out$glo.SecCons)
glo_cat_out$glo.Rating = as.factor(glo_cat_out$glo.Rating)
glo_cat_out$glo.StockWave = as.factor(glo_cat_out$glo.StockWave)
glo_cat_out$glo.PayType = as.factor(glo_cat_out$glo.PayType)
glo_cat_out$glo.Bid = as.factor(glo_cat_out$glo.Bid)

glo_cat_out = cbind(glo_cat_out, glo_speed, glo_size, glo_debttoval)

names(glo_cat_out)
names(glo_cat_out) = sub("glo.","",names(glo_cat_out))
names(glo_cat_out)
summary(glo_cat_out)

create_report(glo_cat_out)

us_cat_out = as.data.frame(slice(us_cat, as.numeric(rownames(us_temp))))
us_cat_out$us.SameCount = as.factor(us_cat_out$us.SameCount)
us_cat_out$us.SameSec = as.factor(us_cat_out$us.SameSec)
us_cat_out$us.Const = as.factor(us_cat_out$us.Const)
us_cat_out$us.SecCons = as.factor(us_cat_out$us.SecCons)
us_cat_out$us.Rating = as.factor(us_cat_out$us.Rating)
us_cat_out$us.StockWave = as.factor(us_cat_out$us.StockWave)
us_cat_out$us.PayType = as.factor(us_cat_out$us.PayType)
us_cat_out$us.Bid = as.factor(us_cat_out$us.Bid)

us_cat_out = cbind(us_cat_out, us_speed, us_size, us_fcfmarg, us_cashr)

names(us_cat_out)
names(us_cat_out) = sub("us.","",names(us_cat_out))
names(us_cat_out)

summary(us_cat_out)
create_report(us_cat_out)
```

```
###########################################################################
#####
############################REGRESSIONS####################################
#####
###########################################################################
#####

############################ROA############################################
#####

glo_yx = subset(glo_num_fin, select=-c(ROAMean,Short,Long))
glo_yx = cbind(glo_yx,glo_cat_out)
min(glo_yx$ROADiff)
glo_yx$ROADiff = log(glo_yx$ROADiff + 11)
us_yx = subset(us_num_fin, select=-c(ROAMean,Short,Long))
us_yx = cbind(us_yx,us_cat_out)
min(us_yx$ROADiff)

fit_glo_roadiff = lm(ROADiff ~ ., data = glo_yx)
summary(fit_glo_roadiff)
plot(fit_glo_roadiff$residuals)
lmtest::bptest(fit_glo_roadiff)

stargazer(fit_glo_roadiff, title="Regression Results",
          align=TRUE,report = ("vc*p"),
          omit.stat=c("LL","ser","f"), no.space=TRUE)

step_glo_roadiff = stepAIC(fit_glo_roadiff, direction = "both",
                      trace = TRUE)
summary(step_glo_roadiff)
lmtest::bptest(step_glo_roadiff)


fit_us_roadiff = lm(ROADiff ~ ., data = us_yx)
summary(fit_us_roadiff)
plot(fit_us_roadiff$residuals)
lmtest::bptest(fit_us_roadiff)

step_us_roadiff = stepAIC(fit_us_roadiff, direction = "both",
                      trace = TRUE)
summary(step_us_roadiff)
lmtest::bptest(step_us_roadiff)

glo_yx = subset(glo_num_fin, select=-c(ROADiff,Short,Long))
glo_yx = cbind(glo_yx,glo_cat_out)
min(glo_yx$ROAMean)
glo_yx$ROAMean = log(glo_yx$ROAMean + 13)
us_yx = subset(us_num_fin, select=-c(ROADiff,Short,Long))
us_yx = cbind(us_yx,us_cat_out)
min(us_yx$ROAMean)
us_yx$ROAMean = log(us_yx$ROAMean + 13)

fit_glo_roamean = lm(ROAMean ~ ., data = glo_yx)
summary(fit_glo_roamean)
plot(fit_glo_roamean$residuals)
lmtest::bptest(fit_glo_roamean)

step_glo_roamean = stepAIC(fit_glo_roamean, direction = "both",
                       trace = TRUE)
summary(step_glo_roamean)
lmtest::bptest(step_glo_roamean)
```

```
fit_us_roamean = lm(ROAMean ~ ., data = us_yx)
summary(fit_us_roamean)
plot(fit_us_roamean$residuals)
lmtest::bptest(fit_us_roamean)

step_us_roamean = stepAIC(fit_us_roamean, direction = "both",
                      trace = TRUE)
summary(step_us_roamean)
lmtest::bptest(step_us_roamean)

############################SHORT############################################
#####

glo_yx = subset(glo_num_fin, select=-c(ROAMean,ROADiff,Long))
glo_yx = cbind(glo_yx,glo_cat_out)
min(glo_yx$Short)
glo_yx$Short = log(glo_yx$Short + 1)
us_yx = subset(us_num_fin, select=-c(ROAMean,ROADiff,Long))
us_yx = cbind(us_yx,us_cat_out)
min(us_yx$Short)
us_yx$Short = log(us_yx$Short + 2)

fit_glo_short = lm(Short ~ ., data = glo_yx)
summary(fit_glo_short)
plot(fit_glo_short$residuals)
lmtest::bptest(fit_glo_short)

step_glo_short = stepAIC(fit_glo_short, direction = "both",
                       trace = TRUE)
summary(step_glo_short)
lmtest::bptest(step_glo_short)

fit_us_short = lm(Short ~ ., data = us_yx)
summary(fit_us_short)
plot(fit_us_short$residuals)
lmtest::bptest(fit_us_short)

step_us_short = stepAIC(fit_us_short, direction = "both",
                      trace = TRUE)
summary(step_us_short)
lmtest::bptest(step_us_short)

############################LONG#############################################
#####

glo_yx = subset(glo_num_fin, select=-c(ROAMean,ROADiff,Short))
glo_yx = cbind(glo_yx,glo_cat_out)
min(glo_yx$Long)
glo_yx$Long = log(glo_yx$Long + 4)
us_yx = subset(us_num_fin, select=-c(ROAMean,ROADiff,Short))
us_yx = cbind(us_yx,us_cat_out)
min(us_yx$Long)
us_yx$Long = log(us_yx$Long + 4)

fit_glo_long = lm(Long ~ ., data = glo_yx)
summary(fit_glo_long)
plot(fit_glo_long$residuals)
lmtest::bptest(fit_glo_long)

step_glo_long = stepAIC(fit_glo_long, direction = "both",
```

```
                         trace = TRUE)
summary(step_glo_long)
lmtest::bptest(step_glo_long)

fit_us_long = lm(Long ~ ., data = us_yx)
summary(fit_us_long)
plot(fit_us_long$residuals)
lmtest::bptest(fit_us_long)

step_us_long = stepAIC(fit_us_long, direction = "both",
                        trace = TRUE)
summary(step_us_long)
lmtest::bptest(step_us_long)

stargazer(fit_glo_roadiff, fit_glo_roamean, fit_glo_short,
          fit_glo_long, title="Regression Results",
          align=TRUE,report = ("vc*p"), no.space=TRUE)

stargazer(fit_us_roadiff, fit_us_roamean, fit_us_short,
          fit_us_long, title="Regression Results",
          align=TRUE,report = ("vc*p"), no.space=TRUE)

stargazer(step_glo_roadiff, step_glo_roamean, step_glo_short,
          step_glo_long, title="Regression Results",
          align=TRUE,report = ("vc*p"), no.space=TRUE)
stargazer(step_us_roadiff, step_us_roamean, step_us_short,
          step_us_long, title="Regression Results",
          align=TRUE,report = ("vc*p"), no.space=TRUE)
```

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management
Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve, Belgique | **www.uclouvain.be/lsm**