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Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

Corporate Acquisitions and Expected Stock Returns: A Meta-Analysis

Author: Thibault Parreau
Supervisor: Tomáš Havránek, Ph.D.
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Abstract

This thesis aims at investigating the puzzling relationship between corporate acquisitions and expected stock returns by reviewing numerous studies on this topic through the use of state of the art meta-analysis tools. Such an analysis is required because many papers examined this relationship but their results varied. We therefore collected 421 estimates from 20 papers and led multiple regressions to test for the presence of publication bias. Throughout this analysis we indeed found evidence supporting the existence of publication bias. Furthermore, we decided to apply Bayesian Model Averaging to reduce the model uncertainty and find out why our abnormal returns estimates greatly vary across studies. Our results suggest that one of the most important drivers are the standard-error terms. This subsequently proves that publication bias is the most responsible for the heterogeneity amongst our estimates. Our analysis fails to demonstrate any positive effects from M&A activity on a firm post-acquisition performance. We suggest that other motives are under-represented in the underlying theory that aims to assess M&A outcomes.

Keywords Mergers and Acquisitions, Stock Returns, Abnormal Returns, Meta-Analysis, Publication bias

Author’s e-mail thibault.parreau@gmail.com
Supervisor’s e-mail Tomas.havranek@ies-prague.org
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Acronyms

AR Abnormal Returns

BMA Bayesian Model Averaging

BHAR Buy-and-hold Abnormal Returns

CAR Cumulative Abnormal Returns

FAT Funnel Asymmetry Test

M&A Mergers and Acquisitions

MCMC Markov Chain Monte Carlo

OLS Ordinary Least Squares

PET Precision Effect Test

PIP Posterior Inclusion Probability

PMP Posterior Model Probability

WLS Weighted Least Squares
Master Thesis Proposal

Author Thibault Parreau

Supervisor PhDr. Tomáš Havránek

Proposed Topic Corporate acquisitions and expected stock returns: A meta-analysis

Motivation

In 2015, the Institute of Mergers, Acquisitions and Alliances (IMAA) reported that companies worldwide announced over 44,000 transactions of Mergers & Acquisitions, 30 years ago in 1985 this figure was only 2,675. We therefore observe a tremendous increase of corporate acquisitions over the time. Why? Several factors can explain this trend and lead to a growth in investment opportunities: Increased competition, consolidation in many industries, deregulation, expansion of new industries, globalisation, increase of liquidity, etc. This sharp increase is nonetheless not independent from the rise in the number of stock transactions observed over the past years. There is indeed a link between corporate acquisitions and stock returns. However this link is ambiguous, the results of many studies are puzzling. The expected pattern observed over the past few years is that following an acquisition, the stock returns of the acquiring firm decrease on the long run.

The payment of a premium from the bidder can explain this phenomenon. This is the expected intuition which has been proven under certain circumstances in certain period, countries over the times. This is
therefore highly problematic: Why firms would want to engage in M&A if they don’t create any value?

The aim of this master thesis is to therefore investigate the long term post acquisition performance of firms engaging in M&A and see how these firms are impacted: are they obtaining positive or negative returns on average? We as well want to question the literature on the matter and test if there are some publication bias leading results displayed to be negative. To that end, we will lead a meta-analysis. Martin Paldam simply summed up what a meta analysis is in a few words: It is a quantitative survey of a literature reporting estimates of the same parameter.

Hypotheses

**Hypothesis 1:** There is an "AR effect", firms systematically experiment negative abnormal returns following an M&A.

**Hypothesis 2:** The literature estimating the long run abnormal returns of the acquiring firm following an acquisition suffers from publication bias.

**Hypothesis 3:** Newers studies tend to display negative estimates of long term abnormal returns.

Methodology

Before conducting the meta-analysis, the first step is to collect comparable papers displaying long term abnormal returns of firms engaging in M&A (while using the so called ”snowballing“ technique). I mostly used Google Scholar and RePEc to do my research. The aim is to find studies that provide a point estimate and a t-statistic. 20 studies displaying these estimates were collected in order to lead this study. These studies are either published or unpublished papers and book chapters.

Firstly, we will test for the selective reporting bias by using the funnel plot to determine (visually) if there are any reporting bias, to
then better determine (by regressions) if they do actually exist. In the absence of selective reporting bias, the graph should take a symmetrical funnel shape.

In presence of selective reporting bias, the reported estimates will be correlated with their standard errors (and the plot will be asymmetrical). The further specifications we will use to estimate our regression will be the OLS, to then run a panel data regression using both study-fixed effects and between effects, to then use the WLS and finally address the heteroskedasticity issue. We will as well visually test for heterogeneity to then test it by a regression -by using Bayesian Model Averaging- to better investigate if our collected estimates vary.

**Expected contribution:**

My main contribution will be to shed some light on the puzzling relationship linking corporate acquisition and stock returns by reviewing numerous papers on this topic and by employing state of the art techniques, to tackle model uncertainty (with BMA) and to better spot publication bias (with MRA tools). This thesis is therefore the first one to use these two techniques to investigate corporate acquisitions and expected stock returns. I will as well prove that the common intuition on this matter (the AR effect) is biased and why.

**Outline:**

1. Introduction: This section will introduce the topic, highlight the importance of the publication bias and the need to lead a meta-analysis.

2. Literature review: This section will investigate the literature and help answer two questions: What are the reasons leading firms to engage in corporate acquisitions and what are the outcomes for the shareholders of both companies.

3. Frameworks used to estimate the long run abnormal returns: This
section will explain more in details the numerous models used by the authors of the studies incorporated in our list of studies.

4. Data set: We will explain how the data set was found, and how the various studies incorporated into the meta-analysis were obtained.

5. Publication bias: We will introduce the notion of publication bias, how to detect and counter it, why using meta regression techniques and will depict the results of our findings and their implications.

6. Why our AR estimates vary across studies?: Bayesian Model Averaging will be used in this section and will help us understand why our AR estimates vary.

7. Discussion: This section will be dedicated to discuss our results and try to better highlight the challenges raised by corporate acquisitions and stock returns for further research on the matter.

8. Conclusion: We will conclude and summarize our findings.

References:


1 Introduction

1.1 Introducing the topic

This master thesis aims at understanding the puzzling relationship between corporate acquisitions and expected stock returns. Over the past few years, some authors started to mention “expected” stock returns because a pattern emerged: The stocks of the acquiring firms decreased on the long run following the deal. Many reasons come to mind to explain such a phenomenon. One can think that because the bidding firm must pay a premium to acquire the target (purchase the stock prices of the target above its current valuation), the stocks of the target will increase whereas the stocks of the bidder will decrease (their debt capacities increase or they had to incorporate a lot of their cash). It would indeed be wonderful to summarize the outcomes of most M&A deals like this. In reality, it is not. Many factors concerning both the bidder and the target have to be taken into account to fully evaluate the outcomes: size of the target, mode of payment, type of transaction, relatedness of the acquisitions, etc.

When taking all these factors into account, most research tend to display long term abnormal returns to be quasi null or negative for the shareholders of the bidding firm. Agrawal et al (1999) in The post-merger performance puzzle review the literature examining long-run stock returns following acquisitions and conclude that long-run performance is indeed negative following mergers. Although, performance is non-negative following tender offers and even seldom positive. The net increase of M&A deals over the past few years which generated billions of dollars deals and impacted a lot of industry becomes somehow confusing.
The question arising here is why leading such deals if they are not value enhancing? The aim of this master thesis is to therefore better analyze why and how M&A deals create or destroy value based on the literature related to this matter. One can indeed wonder why most authors tend to report quasi null or negative estimates in their studies. The purpose of this study is therefore to investigate the link between corporate acquisitions and expected stock returns. Are all acquirers supposed to experience negative abnormal stock returns? In order to answer this question, we will run a meta-analysis. Somehow, the literature portraying the M&A landscape fails to properly analyze how value is created. Authors can fail to clearly indicate their results because they tend to report undervalued estimates. It can indeed be difficult to assess the economic outcomes of a phenomenon if it is not driven by economic motives.

One of the main hypothesis of the thesis will therefore be the following: What if the literature trying to assess the outcomes of M&A based on economic indicators (stock returns) fail to do so because M&A are not dictated by economic motives? Which later leads to biased results and therefore publication bias. We will therefore try to assess the strength of this possible publication bias and try to find out what really drives corporate acquisitions. Throughout this study we will therefore try to test if there is an "AR effect" following an acquisition, i.e do firms systematically experiment negative abnormal returns following an M&A. We will take into account both corporate acquisitions and corporate mergers since the authors studying long term abnormal returns do not differentiate the two in their estimation.

We will therefore broaden a bit the scope of our analysis and include corporate mergers in order to lead an efficient study. In many papers, the econometric models used are the same (or almost), so are the regressions but not the data used. The authors of these papers can lead the study in one way or another to confirm their initial theory. There are therefore several publication bias, some are bigger depending on the journal it has been published in. That is why a meta-analysis is required.
Martin Paldam (2015) in Meta-analysis in a nutshell: techniques and general findings, simply summed up what a meta-analysis is in a few words: It is a quantitative survey of a literature reporting estimates of the same parameter. The estimates at stake here, are long-term abnormal returns, in order to determine if there is an “AR effect”. We will explain later, why and how the data collection has been realized.

This study will be organized as follow: The second section of this chapter: Motivation, will be dedicated to explain the motivation of the topic. We will define and better understand M&A deals, the need to lead acquisitions, their benefits and their impact on the stocks of the acquiring firm. The second chapter: Literature review, will investigate the M&A literature and help answer two questions: What are the reasons leading firms to engage in corporate acquisitions and what are the outcomes for the shareholders of both companies. We will summarize the main findings and highlight the issues raised by the authors over the past few years. The third chapter: Frameworks used to estimate the long run abnormal returns, will explain more in details the numerous models used by the authors of the studies incorporated in our list of studies.

The fourth chapter: Data set of our study, will explain how the data set was found, and how the various studies incorporated into the meta-analysis were obtained. The fifth chapter: Publication bias, will introduce the notion of publication bias, how to detect and counter it, why using meta regression techniques and will depict the results of our findings and their implications. We will display the results of our meta-regressions and follow the work of Astakhov et al (2017) and Havranek & Irsova (2012). The sixth chapter: Why our AR estimates vary across studies? will introduce a new tool: BMA and will lead us to find out if there is some heterogeneity amongst our AR estimates. We as well follow the work of Havranek et al (2015). The seventh chapter: Discussion, will be dedicated to discuss our results and try to better highlight the challenges raised by corporate acquisitions and stock returns for further research on the matter. The eight chapter: Conclusion, will conclude and summarize our findings.
1.2 Motivation for the topic:

Many strategies can be targeted by firms whenever they want to reach an higher growth and expand their operations. In this fashion, this growth can be either achieved internally or externally. Organic growth (e.g. internal) is typically depicted as an increase in revenue that is driven by a firm’s internal business capabilities and can be achieved through numerous ways. This can be done thanks to marketing improvements via increasing market shares by promoting products and improve the brand image. As well, innovation and product development are concerned, the firm needs to develop new products in order to reach new markets or gain new shares on current ones. The sales and distribution segment is also important, sales can be improved by expanding sales operations and finding new distribution partners. The main operations can play a huge part by reducing costs through operational efficiency. Finally at the end of the process, the customer segment is crucial, the customer experience always needs improvement and feedbacks need to be taken into account.

Many businesses target these 5 pillars to strengthen their market shares. Nevertheless, inorganic growth (e.g. external) became very popular over the past few years, many firms were eager to expand their assets quickly, improve their market presence, achieve higher income and take advantage of possible synergies. In this fashion, corporate acquisitions evolve dramatically.

In 2015, the Institute of Mergers, Acquisitions and Alliances (IMAA) reported that companies worldwide announced over 44,000 transactions of Mergers & Acquisitions with a total value of $4.5 trillion. Thirty years ago in 1985 this figure was only 2,675. We therefore observe a tremendous increase over the past few years. Several factors can explain this trend: Increased competition, consolidation in many industries, deregulation, expansion of new industries, globalisation, increase of liquidity, etc.

Corporate acquisitions can take various ways: Merger, tender offer, acquisition of assets and other acquisitions. Basically, a merger is an agreement that unites two existing companies into a new one. Meanwhile, a tender offer is an offer to purchase some or all of shareholder’s shares...
in a company. The price offered is usually at a premium to the market price. The board of directors approves the transaction. As opposed, an hostile takeover is often unexpected and many defense mechanisms are set up by the board to counter it. Acquisition of assets typically occur when a company goes bankrupt, other firms can then engage in buyout strategies in which key assets of the targeted bankrupt company are purchased rather than its shares. Syal and Chikkara (2017) highlight that the purpose of corporate acquisitions is to serve the growth strategy of one firm by accessing new markets, acquire foreign strategic assets, enhance R&D efforts and the most important aspect, to create value for shareholders. While many objectives are met, the latter one is not. This is rather surprising, but most of the corporate acquisitions are destroying value for the shareholders. Why? And how? The M&A lifecycle shows us that the last stage is the most important: the Integration stage. This step is crucial, in case of failure it could destroy value for the shareholders of the acquiring firm.

The Post-merger integration is the process of combining and restructuring the business to realize value from the M&A. To this end, several leverages can be pulled to better integrate the new entity. Haspeslagh and Jemison (1991) developed the acquisition integration model and stress that criteria must be met in order to successfully integrate the new entity: There is a need for strategic interdependence and a need for organizational autonomy. Basically, to answer the first need, the acquiring firm must understand how the transaction can be value-enhancing and need to create value through several ways. Firstly, by sharing the resources via combining the two entities at the operational level. Secondly, by transferring the skills, value can be conceived by moving the workforce, or sharing crucial information, know-how and knowledge. Thirdly, there is a need to re-think the general management of the new entity, value can therefore come from a better control or an improved insight.

Finally, there must be a combination of the benefits, meaning that the new entity must have an overall better borrowing capacity, better market power and cash resources.
On the other hand, they precise that the need for organizational autonomy can be fulfilled by answering three basic questions: Is autonomy essential to preserve the strategic capabilities we bought? If yes, how much autonomy should be allowed? And finally, in which areas specifically is autonomy important? Therefore, once these factors have been thoroughly examined and scored, four acquisition integration approach can be considered: Absorption, preservation, symbiosis and holding.

Nevertheless, the estimated failure rate after an acquisition goes from 60 to 80%. This leads Bruner (2003, p. 2) in Does M&A Pay? to point out that

"The sobering reality is that only about 20% of all mergers really succeed. Most mergers typically erode shareholders wealth... The cold, hard reality is that most mergers fail to achieve any real financial returns."

This situation needs some contrast. Indeed, most research studying corporate acquisitions and stock returns conclude that on average, the target firms usually experience positive abnormal returns, while the bidder firms experience negative (or 0) abnormal returns.

We will investigate the long term abnormal returns from the acquirer side and try to question whether this expected pattern holds under several circumstances- what we established previously as the «AR effect». After having properly highlighted what is at stakes whenever a company decides to engage in M&A deals, we will now better investigate how the literature relates to this topic with the next chapter.
2 Literature review

2.1 Antecedents leading to M&A

We will divide this literature review into two categories. Firstly, we will summarize why firms turn to external growth and engage in corporate acquisitions to then explain how these corporate acquisitions can (or cannot) be value enhancing for the acquirers.

In Taking stock of what we know about Mergers and Acquisitions: A review and research agenda, Halebian et Al (2009) categorizes four acquisition antecedents that lead firms to acquire: Value creation, managerial self-interest (value destruction), environmental factors, and firm characteristics. The first category depicts many reasons which lead to corporate acquisition. The first one is market power, which could be considered as an attempt to appropriate more value from customers. Having fewer firms in an industry will then increase the firm-level pricing power. Acquisitions can as well be seen as efficiency enhancing. McGucking et Al (1995) claim in their studies that acquisitions result into improving the productivity on the long run.

Furthermore, the resource redeployment argument is also supported by many scholars stating that managers view horizontal acquisitions as a mean of facilitating redeployment of assets and competency transfers to generate economies of scope. Finally, some research proved that acquisitions can be seen as a tool to discipline ineffective managers. Jensen (1986) stated that acquisitions can help protect shareholders from poor management.
While many researchers proved that the purpose of corporate acquisitions is higher growth and value creation for the shareholders, many, on the other hand showed that entrenched managers appear to engage in acquisitions in order to maximize their private benefits and destroy value for the shareholders. Many managers are indeed incentivized to produce higher profits and gain market shares by various compensation schemes, such as stock options.

Agrawal et Al (1994) demonstrated that industries involving higher CEO compensations are also more engaged in corporate acquisitions. As well, managers from the bidding firms are positively rewarded for taking part in such activities. Many studies depict that entrenched managers are seeking to build empire by achieving many acquisitions in order to improve their reputation, firm size, get higher salaries and therefore increase their private benefits. Which is what Roll (1987) theorized as the “managerial hubris”. Which later leads to overpay for targets and can generate negative returns.

Some environmental factors can also lead to corporate acquisitions. Some kind of herding effect can take place in the M&A landscape, managers tend to duplicate what their competitors are doing. Therefore, if competitors decide to expand their operations in another country or absorb their supplier or companies outsourcing their production, managers will tend on average to repeat this scheme. Indeed, Haunschild (1998) showed that numerous acquisitions were positively related to the number of acquisitions completed by interlock partners.

Finally, some firms can be tempted to pursue acquisitions due to their success. The experience in previous acquisitions realized is indeed important. History tends to repeat itself in the M&A history, firms are indeed more keen to turn to either horizontal, vertical, product extension acquisitions if they were successful by doing so in the past (Haleblian et al, 2006).
Again, if one company decided to absorb the supplier of one of their products, they will tend to absorb the other ones in their portfolio of product or services. Nevertheless, as Roll (1986, p. 197) stated in The Hubris Hypothesis on Corporate Takeovers:

“Despite many excellent research papers, we still do not fully understand the motives behind mergers and tender offers or whether they bring an increase in aggregate market value.”

Despite many motives that lead to create a new entity, it is unclear whether corporate acquisitions benefit to the shareholders of both firm and increase the post performances of the new entity created. It would be therefore beneficial to understand under which conditions, M&A can destroy or create value.

2.2 How M&A can destroy or create value for the shareholders

The method of payment used by the bidding firm appears to be somehow crucial. Whenever the firm is confident regarding its current valuation, cash is going to be offered for the transaction whereas, when the firm sees itself as overvalued or is uncertain regarding the target shares valuation, shares are going to be offered (Franks et al, 1991). Several studies tend to confirm that cash offers lead to successful M&A and positive returns for the bidding firm, whereas it is the opposite in share offers. The mode of acquisition is also determinant. A friendly merger with shares tend to create less value than a tender offer with cash, which are globally hostile (Agrawal et al, 1992).

Several scholars point out another aspect of the operation, whether the acquisition is related or unrelated to the core business of the bidding firm. Therefore, unrelated acquisitions can waste cash-flows on bad acquisitions and lead to value destruction, whereas related acquisitions tend to create value on average (Jensen, 1986). The corporate governance of the target is also relevant.
A strong board with independent directors, separate chair and CEO and a strong blockholder will on average better monitor the designated managers and lead to create more value (Fama et al, 1983). Finally, the size of the target is also determinant. A bigger target could indeed bring more synergy and more assets but could as well be more complicated to manage and more expensive (Fuller et al, 2002). Scholars are therefore divided on this matter, whether acquiring a bigger target is value-enhancing or not. Despite many motives that lead to create a new entity, it is unclear whether corporate acquisitions benefit to the shareholders of both firm and increase the post performances of the new entity created.

Roll stated that decision makers in acquiring firms pay too much for their targets on average, and that around a takeover, three phenomena appear to be proven:

(1) The combined value of the target and bidder should decrease slightly;

(2) The value of the bidding firm should decrease;

(3) The value of the target firm should increase.

These assumptions have been proven on average over the years in many studies. It leads us to wonder then, why acquirers tend not to experience positive abnormal returns following the merger? The motives to acquire are clear, but they seem not to benefit from this operation. Furthermore, the type of payment appears somehow crucial. Several studies demonstrated than stock financed acquisitions lead to negative returns for the bidder while cash financed acquisitions appear to be less detrimental.

Jensen and Rubac, (1983), in their classic survey of the empirical research in this area, summarize the results of 6 studies that examine the returns to bidders in the years following the takeover. The evidence shows that after tender offers, the target firms can earn insignificant positive abnormal returns while after mergers, bidding firms systematically underperform. They therefore join the analysis of Roll.
In this fashion, in Glamour, value and the post-acquisition performance of acquiring firms, Rau and Vermaelen (1997) are trying to better assess the link between acquisitions and returns. They state that bidders in mergers under-perform while bidders in tender offer over-perform in the 3 years after the acquisition.

However, the long-term underperformance of acquiring firms in mergers is predominantly caused by the poor post-acquisition performances of low-book-to market “glamour” firms. They specify that both the market and the management over extrapolate the bidder’s past performance when they assess the desirability of an acquisition. This paper has therefore two ambitions: Examine the bidder’s underperformance in the long-run after the acquisition and then find out the determinants of this underperformance.

They therefore adjust for both firm size and book-to-market effects and to explain the cross-sectional variation in long run bidder returns, they examine three hypotheses:

1. The performance extrapolation hypothesis;
2. The mean of payment hypothesis;
3. The EPS myopia hypothesis.

The first hypothesis states that the market over extrapolates the past performance of the bidder when it assesses the value of an acquisition. Managers and other decision makers who have to approve an acquisition, receive feedback on the quality of the bidder’s management from the market. In firms with low book-to-market ratios (the glamour firms); the managers are more likely to overestimate their own ability to manage an acquisition (e.g they are infected by hubris).

Glamour firms are characterized by high past stock returns and high past growth in cash flows and earnings which should strengthen the management’s beliefs in its own actions. Meanwhile value firms are firms with high book-to-market ratios, where management and boards will be more cautious before approving an acquisition. As the acquisition becomes more and more clear, the market has to re-assess the quality of the bidder.
Consequently, in the short run, around the announcement of the acquisition, glamour bidders will experience higher abnormal returns than value bidders and in the long run this performance will reverse.

The second hypothesis is stating that when acquisitions are paid with shares, the stocks of the bidder firm are overvalued. Hence, on average, long-run abnormal returns to bidders will be negative in shares-financed acquisitions and positive in cash-financed acquisitions. Finally, the third hypothesis is showing that mergers with a positive impact on EPS (earnings per share) will perform the worst. If the EPS increases after the acquisition, this means that a high premium has been paid, the market will therefore interpret this as an overpayment and negatively reacts. The results are showing that the performance extrapolation is more consistent and this paper concludes that value bidders outperform glamour bidders in the 3 years after the tender offer.

2.3 Summary of the previous meta-analyses led on M&A:

In this section, we will try to summarize other meta-analyses led in the same field. There are indeed a few meta-analyses trying to investigate the success of M&A. In Meta-analyses of Post-acquisition Performance: Indications of Unidentified Moderators, King et Al (2004) are studying financial post-acquisition performances. They rely on 4 variables to assess it:

1. Acquisitions realized by a conglomerate firm;
2. Acquisitions of a related firm;
3. The method of payment used;
4. Whether the acquiring firm had prior acquisition experiences.

They state that both acquired and acquiring firms realized positive abnormal returns on the day of an announcement (day=0) and suggest that M&A activity will create long term synergies.
Nevertheless, the further results state that the day 0 returns for acquired firms are extremely high while the returns over the same period for acquiring firms are much lower. The returns for acquiring firms for day 1 and later are either insignificant or negative. Acquiring firms are therefore not incorporating the benefits of the expected synergy.

Their precise results is rather surprising: Continuing holding equity in acquiring firms will lead to significantly negative abnormal returns beginning 22 days after an acquisition is announced. In a nutshell, they find no evidence that acquisition, on average, improve the financial performances (abnormal returns, accountings performances) of acquiring firms after the day completed acquisitions are announced.

They basically conclude that acquisitions either have no significant effect or a modest negative effect on an acquiring firm’s financial performances in the post-announcement period. The existing empirical research has not clearly identified the variables that impact an acquiring firm’s performances. The results indicate that post-acquisition performance is moderated by unspecified variables. The 4 factors stated above (and mostly used in the research) do not fully explain the performances after acquisition. In fact, the wide variance surrounding the association between M&A activity and subsequent performance suggests that subgroups of firms do experience significant and positive returns. The existing models have simply failed to clearly identify these subgroups.

Non-financial motives are surely under-represented in theory and research that seek to explain M&A trends. They can indeed be motivated by other factors than financial performances such as: Managerial motives or technological uncertainties, etc... To briefly sum up the findings of the authors, the cumulated results of the previous research highlight that the conditions most commonly studied in M&A (e.g the 4 financial motives) do not impact post acquisition performances. What impacts the financial performances of firms engaging in M&A remain largely unexplained.
In the same fashion, in Factors influencing wealth creation from Mergers and acquisitions: a Meta-Analysis, Datta et al (1992) employ a multi-factor model in order to investigate what creates wealth following an M&A. The determining factors are: the regulatory changes, the number of bidders, the type of transaction, the mode of payment, and the type of acquisition. Their main findings are quite similar to other studies reviewed previously. Returns to bidders declined over time whereas targets realize gains. Bidders gain in non conglomerate acquisitions but lose in multiple bid situations and in transactions financed by stocks, whereas targets gain more in tender and lose gains in transactions financed by stocks. On the other hand, their conclusions are quite interesting, in the M&A landscape, it is far more advantageous to be a seller than a buyer since the targets benefit more from the operation on average. Furthermore, the shareholders from a target firm can maximize their returns by refusing stock financed deals and being purchased by a bidder from an unrelated industry.

However, bidders should as well apply this advice for two reasons: it speeds up the overall process and sends a positive signal to the capital market. Bidders should therefore have a large amount of cash in order to lead acquisitions. The authors therefore advise to lead further research by associating investment and financing decisions since both are linked.

In Do M&A deals create or destroy value? A meta-analysis, Meckl et al (2016) led the most recent meta-analysis on this topic. In addition to the meta-analysis, they incorporate additional factors influencing the performance of M&A transactions using a moderator analysis. Their meta-analysis incorporates 33 studies mostly using short-term event window and investigate the outcomes of 55 399 transactions between 1950 and 2010.

They prefer to incorporate studies published from the year 2004 in order to display recent results. They collect estimates of CAR (Cumulative Abnormal Returns) but prefer to collect short-term estimates with an event window of approximately 41 days.
Furthermore, their moderator analysis include the type of M&A transaction, the year of publication of the study and the event window of the CAR. Their results indicate that only 47.6% of all M&A transactions worldwide are successful. They found out that cross-border transactions are more successful than domestic transactions. Furthermore, their paper displays several implications. They indeed advocate that risk management should be better taken into consideration and that it oversees the success of factors influencing an M&A deal. A better risk management framework could indeed cheer the confidence of the capital markets and increase the success rate of the operation. They also recommend to better complete the due diligence phase in order to properly assess the target. They found out that on average, bidding firms tend to misevaluate their targets and the risks associated to this kind of transaction.

In Meta-analyses of the performance implications of cultural differences in M&A: Integrating strategic, financial and organizational perspectives, Stahl et al (2008) are trying to assess whether cultural differences impact the outcomes of M&A. They are therefore trying to assess the post acquisition performances of acquiring firms not based on financial motives- as done above- but based on social, cultural and psychological factors which impact the new entity created. Such factors can be cultural similarities, management style, the pattern of dominance between the two firms, the social climate before and after the operation, the transfer of knowledge and know-how, the transfer of skills of people, etc. The authors prefer to incorporate the cultural differences (and related variables linked to management style).

Their results are not quite significant, they do not find neither a negative or positive effect of cultural differences on the performance of M&A. Nevertheless, they invite future researchers to try to investigate how cultural differences can impact the Integration of the two firms. As we mentioned before, two entities can fail to properly merge if their corporate cultures are too different. Which was one of the reasons the merger between AOL and Time Warner failed.
The last one was conducted by Homberg et al (2009) in Do synergies exist in related acquisitions? A meta-analysis of acquisitions studies. They try to assess whether relatedness is a source of potential synergies. They define a related transaction if the two entities display similarities in their business field, corporate culture, technologies used or company size. They incorporate 67 studies in their meta-analysis.

They are trying to determine the degree to which shareholders wealth can be explained by business, culture, technological and size relatedness. They found out that the commonly known sources of synergies seem to only have a small impact and that relatedness does not automatically increase the wealth of the shareholders. They conclude that related transactions do not seem to have any positive effect on the outcome of an M&A.

However, to better understand the puzzling relationships between acquisitions and expected stock returns, we must go deeper into this subject and be more precise. We will therefore analyze and summarize the main tools used by the authors to estimate long run abnormal returns in the next section. We will then better understand how to collect these AR estimates in order to build our data set.
3 Frameworks used to estimate long run abnormal returns

3.1 Frameworks used to estimate long run abnormal returns

To better understand how M&A shape the expected stock returns from the bidder’s side, several researchers developed various frameworks. Two main ones are used: Real option models and event studies.

Many authors used real option models to analyze the outcomes of M&A. Basically, real options are all the choices a company can undertake in order to grow (organically, externally), expand or curtail projects based on changing market conditions (could be as well economical, technological). This streamline of literature was originally launched by Margrabe (1978) when he modeled takeovers as exchange options. In his model, timing is exogenous, whilst the takeover activity involves a zero-sum game. This model was later used and changed by Lambrecht et Al (2004) with an endogenous timing.

Hackbarth and Al (2008) chose to model the operating options available to the new entity after the takeover, in order to distinguish growth opportunities mergers and divestitures mergers. Furthermore, the model characterizes the dynamic behavior of stock returns through the merger operation. Their paper is the first one to examine the impact of takeovers on stock returns and on firm-level betas.
On the other hand, the other main dominant framework used deals with Standard event study methodologies. Briefly, an event study is a statistical method to assess the impact of an event (here M&A) on the value of a firm (e.g. the impacts on the stock returns).

This methodology was used for the first time by Fama in 1969. It is used in order to determine the values of the Abnormal Returns (AR) and the Cumulative Abnormal Returns (CAR) for one sample of bidder firms. Authors basically detail their methods, the form of the daily returns they use (discrete or logarithmic), how abnormal returns are calculated, the length of estimation and of the test periods, the ways used to aggregate the returns and finally the t-statistics and the methods of mean comparison used. Most of the studies that estimate stock returns following an acquisition employ this event study technique.

Our sample of studies includes event studies with a particular observation period, e.g. a long term approach. The analysis of abnormal returns can go to 2 or 5 years after bid announcement or its execution.

The profits or losses shareholders experienced after the deal is made are measured through abnormal returns. As Perepezko (2007) depicts in Event Study in the evaluation of effects of M&A:

“The essence of this measure is to relate the wealth of investors holding shares in the acquiring or target company over the observation window to the normal returns in an “ordinary” period when no effects related to the event were reported.”

### 3.2 How to compute the abnormal returns

The abnormal return of one company \(i\) is actual less expected return on the share of company \(i\) over a period \(t\), the formula is as follow:

\[
AR_{it} = R_{it} - E(R_{it})
\]  
(3.1)
where: $AR_{it}$ is the abnormal return for company i over period t; 
$R_{it}$ is the return for company i over period t; 
$E(R_{it})$ is the expected normal return for company i over period t; 
t is the day or month, depending on the data accepted for calculations and unit of the event window.
Consequently, if the abnormal return for one stock i in the event window t is greater than 0, the acquisition is generating wealth for the shareholders of the company i. If the abnormal return equals to 0, the effect of the acquisition is neutral for the shareholders. If the abnormal return is negative, this leads to a loss for the shareholders. The sample of studies for our meta-analysis will only examine long run post acquisition performances and will therefore refer to two measures of abnormal returns: Cumulative abnormal returns (CAR) and Buy-and-hold abnormal returns (BHAR).

Firstly, CAR is calculated as a sum of monthly returns over the analysed period. CAR for company i over the time period t are calculated as follow:

$$CAR_{iT} = \sum_{t=1}^{T} AR_{it}$$ (3.2)

where: $CAR_{iT}$ is the cumulative abnormal return for company i over time period T; 
$T$ is the observation period, time period measured in months; 
$AR_{it}$ is the abnormal return for company i over period t.

Secondly, BHAR is calculated as the return on a buy-and-hold investment in company i, that is to say, from the starting day of the window (e.g the moment of purchase) until the ending day of the window less the expected return on a buy-and-hold investment in a reference portfolio or control firm, as in the formula below:
\[ BHAR_{iT} = \prod_{t=1}^{T} 1 + R_{it} - \prod_{t=1}^{T} 1 + E(R_{it}) \]  

(3.3)

where: \( BHAR_{iT} \) are the buy-and-hold abnormal returns for shares \( i \) over time \( T \);

\( R_{it}, E(R_{it}), t, T \) are as described above.

Consequently, in order to measure the value of the abnormal return, the actual return should be calculated firstly and then the expected return. The actual return is easily calculated, meanwhile there are several ways to estimate the expected return.

There are more several models estimating the expected returns, here are the most popular ones: The Market Model (MM), the Mean Adjusted Return Model (MeAM), the Market Adjusted Return Model (MaAM), the Capital Asset Pricing Model (CAPM), the Matched Portfolio Benchmark (MP). One of the most used benchmark to calculate AR is the Market Model benchmark. Chatterjee et Al (2011) detailed all the steps. It stipulates that stock returns are generated according to the following ordinary least squares equation:

\[ NR_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt} \]  

(3.4)

Where: \( NR_{jt} \) is the normal rate of return for the company \( j \) on the day \( t \);

\( R_{mt} \) is the rate of return for market index \( m \) on the day \( t \);

\( \beta_j \) is the estimated beta of the company \( j \);

And \( \varepsilon_{jt} \) is a mean zero independent disturbance term in period \( t \).

The main advantage of this model is that it leads to smaller variances of AR, which then leads to more powerful statistical tests. Here, the coefficient \( \alpha_j, \beta_j \) are the ordinary least squares parameters of the intercept and slope, respectively for one company \( j \). One must as well
determine one market index to go further and an estimation period. Which leads us to determine the abnormal returns $AR_{jt}$ for one company:

$$AR_{jt} = R_{jt} - (\alpha^j + \beta_j R_{mt}) \quad (3.5)$$

Where: $AR_{jt}$ is the Abnormal Return for company $j$ on day $t$; $R_{jt}$ is the return for company $j$ in day $t$; $\alpha^j$ is the estimate of ordinary least square parameter of intercept; $\beta_j$ is the estimate of ordinary least squares parameter of slope; $R_{mt}$ is the rate of return for market index $m$ on day $t$.

The market model has been used in several papers studying the impacts of acquisitions on stock returns. In order to fully capture the impact of acquisitions on stock returns, we do not restrict our sample to the studies uniquely using event studies. We as well include research papers reporting any form of regression of CAR and BHAR. Our main goal is to collect point estimates and standard errors from the studies satisfying the criteria described above, to then better test for the selective reporting bias. We will later explain how we incorporate the specification (5) in our regression equation.

After having acknowledged how the AR coefficients are estimated we will now see how our data set has been created in the next section.
4 The Data set of our study

4.1 Data collection

In order to lead an efficient meta-analysis, it is required to collect every studies investigating the phenomenon in question- in our case the papers investigating long term abnormal returns following an M&A- to then construct a data set. Once these primary econometric studies are collected, we need to define a precise inclusion criteria to include these studies in our data set. To be included in the data set, the study must satisfy two criteria. Firstly, the study must depict estimates of long term abnormal returns following a corporate acquisition, or a merger. We do not restrict our sample of studies to a particular time period or a particular geography. Secondly, the study must include a thorough description of the methodology applied with the results of the econometric analyses led alongside measures of statistical significance, such as t-statistics, p-values and standard-errors. The data set has been established by searching the following key words: “Acquisitions”, “M&A”, “stock returns” in Google Scholar and RePEc. Our search had many hits, the M&A literature is indeed very broad so we had to narrow it, especially to dissociate the long term and short term abnormal returns.

We therefore carefully read the entire study in order to have the information matching our request to then better assess the consistency of the empirical studies. We as well paid a lot of attention to the bibliography of the papers in order to find additional studies to include to our data set, the so called “snowballing technique”. 
Although our search has been effective and we obtained efficient results, one of the main obstacles we encountered was linked to the variety of models and estimates used by the authors of the papers selected. Indeed, certain authors depict their abnormal returns estimates through various frameworks, CAR (Cumulated abnormal returns), BHAR (Buy and Hold abnormal returns), or through various models, MM (Market Model), FF (Fama French model), etc. This therefore led to a somehow unbalanced data set. In order to counter this, we decided to design weights to all estimates in order to give the same emphasis to each study. We finished this search in August 2018, by including 20 studies in our data set. All the studies combined together obtained almost 7000 citations on Google Scholar, which proves the scientific impact of the literature estimating the AR following an M&A.

The complete list of studies is described below in Table 4.1. The data set includes both published and unpublished studies depicting 451 observations. The first estimate was reported in 1978, while the latest in 2016. Almost all the studies were published in peer-reviewed journals, only three are book chapters.

|-------------------|-----------------------|-------------------|-------------------|----------------|
4.2 Characteristics of the data collected

We chose to incorporate 14 explanatory variables to lead this meta-analysis. We can categorize them in three groups: Estimation characteristics, Publication characteristics and Data specification. The variables selected should help us explain the heterogeneity among the estimates. The variables are detailed as follow:

AR: The reported estimates of the abnormal returns. As explained below, this coefficient is drawn from the coefficients of CAR- Cumulated Abnormal Returns, BHAR- Buy and Hold Abnormal Returns, and AR-Abnormal Returns, and depend from the frameworks used by the authors.

SE: It corresponds to the estimated Standard-Error of the abnormal returns estimates.

PubYear: It corresponds to the year the study has been published. When we had to deal with book chapter or unpublished papers, this variable represents the year when the study first appeared in the databases, could be in the form of a working paper.

StartYear: It is the first year of the data sample which was used for the abnormal returns estimation in the primary studies

EndYear: It is the last year of the data sample which was used for the abnormal returns estimation in the primary studies

n: The number of observations used for the model estimation in the primary study.

t-statistic: It corresponds to the estimated t-statistics of the abnormal returns estimates.

Impact: It is the SciMago journal rank based on the impact factor extracted from Scopus. It is generally defined as a measure reflecting the yearly average number citations to recent articles published in an academic journal.

Cits: It stands for the number of Google Scholar citations from the study.
**ISE:** Dummy variable equal to one if the data selected are from the International Stock Exchange.

**NYSE:** Dummy variable equal to one if the data selected are from the New York Stock Exchange.

**CRSP:** Dummy variable equal to one if the data selected are from the Center for Research in Security Prices.

**BHAR:** Dummy variable equal to one if the authors report BHAR-Buy and Hold Abnormal Returns- estimates.

**CAR:** Dummy variable equal to one if the authors reports CAR-Cumulated Abnormal Returns- estimates.

**MM:** Dummy variable equal to one if the authors use the Market Model or derive their model from the MM.

**CAPM:** Dummy variable equal to one if the authors use the Capital Asset Pricing Model or derive their model from the CAPM model.

**FF:** Dummy variable equal to one if the authors use the Fama-French model or derive their model from the FF model.

**OLS:** Dummy variable equal to one if one of the econometric techniques used for estimation are the Ordinary Least Squares.
### 4.3 Data description

Table 4.2: Description of the explanatory variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std.dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Publication characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t-statistic</td>
<td>0.048</td>
<td>3.91</td>
</tr>
<tr>
<td>StartYear</td>
<td>1974.8</td>
<td>23.62</td>
</tr>
<tr>
<td>EndYear</td>
<td>1991</td>
<td>22.89</td>
</tr>
<tr>
<td>n</td>
<td>206.9</td>
<td>135.8</td>
</tr>
<tr>
<td>AR</td>
<td>-1.46</td>
<td>3.98</td>
</tr>
<tr>
<td><strong>Standard Error</strong></td>
<td>1.024</td>
<td>1.7</td>
</tr>
<tr>
<td>PubYear</td>
<td>2002.6</td>
<td>9.6</td>
</tr>
<tr>
<td>Impact</td>
<td>1.59</td>
<td>2.11</td>
</tr>
<tr>
<td>Cits</td>
<td>252.9</td>
<td>357</td>
</tr>
<tr>
<td><strong>Data Specifications</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ISE</td>
<td>0.12</td>
<td>0.33</td>
</tr>
<tr>
<td>NYSE</td>
<td>0.16</td>
<td>0.37</td>
</tr>
<tr>
<td>CRSP</td>
<td>0.35</td>
<td>0.47</td>
</tr>
<tr>
<td>BHAR</td>
<td>0.24</td>
<td>0.42</td>
</tr>
<tr>
<td>CAR</td>
<td>0.64</td>
<td>0.48</td>
</tr>
<tr>
<td><strong>Estimation characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MM</td>
<td>0.23</td>
<td>0.42</td>
</tr>
<tr>
<td>CAPM</td>
<td>0.27</td>
<td>0.44</td>
</tr>
<tr>
<td>FF</td>
<td>0.09</td>
<td>0.29</td>
</tr>
<tr>
<td>OLS</td>
<td>0.11</td>
<td>0.31</td>
</tr>
</tbody>
</table>
The table 4.2 details all variables we collected from our primary studies along with their summary statistics. The first group of variables describes the characteristics of the publication. The mean reported estimate of the AR coefficient is -1.46 which can intuitively leads us to assume that on the long run, corporate acquisitions lead to negative abnormal returns. We observe as well that the most dominant frameworks used to estimate the AR are either the MM or the CAPM model, half of the authors use them. Authors prefer to display as well CAR estimates over BHAR ones or other forms. Out of the 451 estimates collected from 20 studies, some studies displayed more estimates than others and could therefore bias our study by out-weighting the others and cause more heterogeneity amongst the estimates. To counter this issue, one of the solutions is to give the same weights to all the studies. Each estimate would then be weighted by the inverse of the total number of estimates from the study. The weight assigned to each estimate is: 

\[ W_{ij} = \frac{1}{n_i} \]

Where \( W_{ij} \) is the weight for estimate \( j \) from study \( i \), and \( n_i \) is the number of estimates from study \( i \).

The initial results in the above table indicate not only some strong support of negative stock returns following an M&A as reported in the literature but also the clear heterogeneity of the abnormal returns estimates.

### 4.4 Questionning some possible heterogeneity amongst the data set

We will therefore try to question if there is some presence of heterogeneity amongst our abnormal returns estimates which is driving our coefficients to be quasi-null or negative. We will therefore investigate it visually and then empirically with some regression.

We can visually investigate for the presence of heterogeneity with the help of an histogram displaying the estimates of the long run abnormal returns following an acquisition.
Figure 4.1: The histogram suggests substantial heterogeneity

Note: The figure depicts a histogram of the estimates of the long run abnormal returns following an acquisition.

The reported estimates range from -16.99 to 3.97 with a mean of -1.46. We can visually observe some heterogeneity among our reported estimates and some factors driving our estimates to be quasi null or negative. We can as well question the heterogeneity with the help of the following box-plot. The Figure 4.2 indeed reveals the presence of substantial within and between study variation. We will therefore further investigate the significance of the publication bias in our estimates and some possible heterogeneity in the next chapter.
Figure 4.2: Estimation of the long run abnormal returns vary within and across studies

Note: The figure shows a box plot of the estimates of the long run abnormal returns estimates reported in individual studies.
5 Publication bias

5.1 Understanding the importance of publication bias

The problem of publication bias is most commonly known as the “file drawer problem” Rosenthal (1979) basically describes the tendency of authors to choose not to disclose certain estimates based on various reasons. Studies are being left unpublished in the drawer. We will try to better understand why.

Ones of the best known drivers of publications bias are sponsorship and political influence. The second does not really apply here. We can rather investigate on the side of the journal editors. Indeed, editors are the ones publishing the papers and have the final decision, they can choose to select more suitable results with respect to some expectation or theory. The literature review helped us to acknowledge that one expected pattern tends to emerge on the long run following an acquisition: the long term abnormal returns tend to be negative... Are journal editors therefore incentivized to publish more negative results of the AR coefficients? On the other hand, one other cause of publication bias are directly the researchers. They can voluntary choose not to publish their studies if they do not find the results satisfying or if they believe that these studies will be less likely to get published.

Furthermore, how the study is led and designed also has a huge impact on publication bias. Indeed, the studies estimating small samples are more likely to obtain larger standard errors which consequently leads to results statistically less significant and therefore less likely to get published. As a result, some researchers can have the tendency to apply
multiple models to their data and deliberately choose only to report the significant results, which then leads to alter the evidence in the literature. All these triggers affect the present literature and can be categorized into different publication bias: directional selection and type II selection.

The first one favors a particular direction of the effect observed which makes the subsequent results more likely to get published. The second one favors statistically significant results with larger t-values, no matter the effect aimed. Stanley (2005) pointed out that the type II publication selection along with the heterogeneity of the true effects and misspecification biases cause excess variation among reported effects. In order to avoid any studies distorted toward a specific direction, we need to detect any publication bias. We can effectively do that, first visually with the help of a funnel plot and then empirically with the help of meta regression techniques.

5.2 Detection of the publication bias

In meta-analysis, the funnel plot presents a simple visual representation of a research literature and is one of the most commonly used method to test for the presence of publication bias. Stanley (2005) defines it as the scatter plot of a measure of precision on the vertical axis against the effect size on the horizontal axis.

Precision can be measured as the inverse of the standard error. Applied to our case, on the x-axis is depicted the point estimates of the AR estimates and on the y-axis is depicted the precision of the estimates as the inverse of the standard errors. In case of the absence of selective reporting bias, the graph should take a symmetrical funnel shape, with the most precise estimates concentrated around the underlying mean value of the studied effect, meanwhile less precise estimates are dispersed around the mean.
We therefore can visually witness the presence of selective reporting. The plot appears to be asymmetric with point estimates mostly concentrated on the left side. This suggests mostly negative estimates and therefore indicate that almost null and negative abnormal returns are more likely to get published. It is interesting to witness that some outliers are present (located on the upper right side). This suggests that some AR estimates are positive. On the other hand this is only a visual conclusion, it gives us only a trend. We need to test our assumptions empirically with meta regression techniques. What can drive the asymmetry of the funnel plot as well is the heterogeneity of the abnormal returns estimates due to data drawn from different data samples. Furthermore the skewness of the funnel can as well be triggered, if any misstatement occurred in the primary studies gathered such as omitted variables or mistakes in the estimation technique.

Figure 5.1: The funnel plot

Note: The solid vertical line displays the sample mean, the dashed vertical line displays the sample median.
5.3 Testing publication bias with meta-regression techniques

As mentioned previously, publication bias can be observed graphically through the use of a funnel plot and then corrected using Meta-Regression Analysis techniques. As Stanley (2005) stated, MRA can be used to model publication selection and statistical power and to circumvent its effects. Following Stanley, we will use an MRA model that captures the relationship between the effect from the primary studies and their standard errors. We will use the equation (5) from Chapter 3. The regression equation will then have the following form:

\[ A_{jt} = A_0 + \beta_0 \cdot SE(A_{jt}) + \varepsilon_{jt} \]  \hspace{1cm} (5.1)

where: \( A_{jt} \) is the i-th estimate of the abnormal returns effect. \( A_0 \) is the underlying mean effect corrected for the reporting bias. \( SE(A_{jt}) \) is the corresponding Standard Error for \( A_{jt} \). \( \beta_0 \) is the coefficient measuring the magnitude and direction of publication bias and \( \varepsilon_{jt} \) is the error term.

Stanley indicates that in the best possible setup, the effects from the primary studies should vary randomly around the underlying mean effect (\( A_0 \)) and be independent from their standard errors.

Which further means that the \( \beta \) should be statistically not different from 0. Therefore, if the publication bias is present, it will be proportional to the Standard Error terms \( SE(A_{jt}) \). However, if we do not impose any further restrictions to our regression equation we will encounter some obstacles. Indeed, the error terms \( \varepsilon_{jt} \) are likely to be heteroskedastic if we use the OLS estimation. Each primary studies incorporated into this meta-analysis use different sample sizes and modelling specifications as described above, which as a result will alter the size of each \( \varepsilon_{jt} \) and vary with studies, which will lead the variance of \( \varepsilon_{jt} \) to be unconstant and violates the OLS assumption of independent and identically distributed errors \( \varepsilon_{jt} \).
Such a situation will bias our analysis, with altered standard error terms which will affect the confidence intervals, t-statistics and p-value. We will therefore apply several techniques which will prevent any heteroskedasticity.

Firstly, we use standard errors clustered at the study level in order to properly run an OLS regression. Therefore, we will still assume zero conditional mean of our error terms $\varepsilon_{jt}$ corresponding to the AR effect $j$ from study $t, E[\varepsilon_{jt}|x_{jt}] = 0$ with still allowing at the same time, more flexibility in the variance-covariance matrix. As a result, we will cluster $E[\varepsilon_{hj}u_{ij}^j|x_{hj},x_{ij}] = 0$ unless $j = j'$, where $x_{ij}$ is a vector of independent variables, applied to our case just $SE_{ij}$.

Secondly, we will run a panel data regression using study-fixed effects and between effects. It leads us to add a second random error term to our model. It will capture the same characteristics that are constant within the estimates from the same study yet are allowed to vary across studies.

Our model will take the subsequent form:

$$A_{jt} = A_0 + \beta_0 SE(A_{jt}) + v_{jt} + \varepsilon_{jt} \quad (5.2)$$

Where: $v_{jt}$ is a vector of study-specific effects which is assumed to be independently distributed as $N(0, \sigma^2)$ and independent of both $SE(A_{jt})$ and $\varepsilon_{jt}$.

Thirdly, we will apply the Weighted Least Squares (WLS) to give more weight to more precise studies. We will need to specify a model for $Var(A_{jt}|SE_{jt})$, estimate it and then apply the OLS to the observations weighted by an estimate of the conditional standard deviation $Var(A_{jt}|SE_{jt})^{\frac{1}{2}}$

The regression will take the form (5.3), with the variable $\frac{1}{SE(A_{jt})}$ used as a weight and which we will designed as precision. We will then follow Havranek et al (2015) and run the specification using the inverse of the number of AR effect estimates reported per study as a weight.

The regression has the following form, here $u_{jt} = \varepsilon_{jt} \cdot \frac{1}{SE(A_{jt})} \sim N(0, \sigma^2)$

46
\[
\frac{A_{jt}}{SE(A_{jt})} = A_0 \cdot \frac{1}{SE(A_{jt})} + \beta_0 + u_{jt} \quad (5.3)
\]

The coefficient from (5.1) are reversed but the coefficient \( \beta_0 \) still bears the publication bias while \( A_0 \) provides an estimate of the underlying mean value of the AR effect. In order to prevent any remaining heteroskedasticity that the weighting has not eliminated, we will estimate this specification with the standard errors clustered. While following these three estimation techniques, we will weight our observations by the number of estimations from each study as described in Chapter 3. To control for the unbalanced dataset we are dealing with. We will apply this to all our model except for the WLS where we use the precision as a weight. We will present the results of each tests in Table 5.1. We will further test for 2 hypotheses inherent to any meta-analyses: the FAT and the PET in order to investigate the publication bias and the effect corrected for it.

The Funnel Asymmetry Test tests the null hypothesis \( H_0 : \beta_0 = 0 \), the publication bias is not present whereas \( H_1 : \beta_0 \parallel 0 \) confirm its presence. Whereas the Precision Effect Test tests the \( H_2 : A_0 = 0 \) and \( H_3 : A_0 \parallel 0 \) and questions the mean value of the abnormal returns estimates after corrections for publication bias. The results are enclosed in Table 5.2.

Furthermore, following Havranek et al (2015), we need to include interaction terms of the standard error with the recursive impact factor (as reported on the IDEAS/RePEc website) and with the year of publication in the specification (5.3). We need to bear in mind that the effect of a study’s publication in a higher-impact journal on the strength of selective reporting bias is highly uncertain: In fact, higher-impact journals have a very strict process to select and publish the papers which reduces the likeliness of misspecification in the studies (such as omitted variables or inappropriate estimation technique).

However, whenever, an author tries to get published in these remarkable journals, his reputation is at stake, therefore he could be afraid to
think outside the box and submit alternative results (with positive AR).

The same pattern applies with the effect on the selective reporting applied to the year of publication: Recent studies apply modern econometric techniques and take lessons from the past studies to deliver significant results with the discovered effect being closer to the true effect.

Nevertheless, the modern papers investigating the link between corporate acquisitions and long term abnormal returns might stick to the expected pattern explained previously: Publishing negative long term abnormal returns and avoid to publish any results that contradict this intuition. The results are enclosed in Table 5.1.

Column 1 in Table 5.1 depicts the baseline result of regressing the AR coefficient estimates and its standard error using OLS. As explained previously, a negative and significant $\beta$ suggests a strong selective reporting bias. We report an estimate of -1.55 here. The estimated constant of 0.132 depicts the underlying mean AR effect corrected for the selective reporting bias and is 11 times smaller in absolute value than the mean of -1.46 reported in Table 5.1.

These results therefore indicate that there is evidence of the AR effect in the data. Column 2 and 3 depicting the results of panel data regression fixed and between effects concur to state that there are possible positive AR estimates and confirm the existence of the outliers observed in our funnel plot previously. Specification (5.3) is being tested using WLS and is depicted in the column 4. It reports the results with the precision variable used as a weight. Taking into consideration these results and the funnel asymmetry test, we can strongly state that there is a selective reporting bias in the estimates of the AR effect.
Table 5.1: Estimating the magnitude of the selective reporting bias

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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<td>BE</td>
<td>Precision</td>
<td>Study</td>
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<tr>
<td>SE</td>
<td>-1.555***</td>
<td>-0.646</td>
<td>1.667***</td>
<td>1.146***</td>
<td>-0.927</td>
</tr>
<tr>
<td></td>
<td>(0.294)</td>
<td>(0.659)</td>
<td>(0.355)</td>
<td>(0.419)</td>
<td>(39.98)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.132</td>
<td>-0.799</td>
<td>0.00452</td>
<td>0.651</td>
<td>0.511</td>
</tr>
<tr>
<td></td>
<td>(0.229)</td>
<td>(0.675)</td>
<td>(0.683)</td>
<td>(0.441)</td>
<td>(40.97)</td>
</tr>
<tr>
<td>Obs</td>
<td>451</td>
<td>451</td>
<td>451</td>
<td>451</td>
<td>451</td>
</tr>
</tbody>
</table>

Note: The table shows the results of regression $A_{jt} = A_0 + \beta_0 \cdot SE(A_{jt}) + \varepsilon_{jt}$ (5.1) where $A_{jt}$-j-th estimate of AR effect reported in study $t$, $SE(A_{jt})$ is the standard error. Specification (1) is estimated using OLS with standard errors clustered by study. Specifications (2) and (3) are panel data regressions with fixed and between effects, respectively. Specifications (4) and (5) are estimated using WLS with precision and reciprocal of number of AR effect estimates reported per study as weight. Standard errors are reported in parentheses. *, **, *** denote significance at the 10%, 5% and 1% level.
In order to further apprehend the pattern of the publication bias, we include in the regression (5.3) the interaction terms of the standard errors with the recursive impact factor and standard error with the year of publication, following the technique used by Havranek and Irsova (2012).

The regression now becomes:

\[ A_{jt} = A_0 + \beta_0 \cdot SE(A_{jt}) + \gamma \cdot SE(A_{jt}) \cdot X_t + \varepsilon_{jt} \]  

(5.4)

Where: \( X_t \) is either an impact factor of the outlet, in which study \( t \) was published, or the year of publication \( t \).

The results are depicted in the table 5.2. The results displayed can appear confusing regarding the effect of journal quality on the selective reporting bias. Indeed, the interaction term of the standard error and the impact factors display a negative sign in column (3) OLS regression and a positive sign in column (4) FE regression. The 2 coefficients are almost non-significant or only at the 5% level.

We can therefore state that in our dataset, the quality of the journal is not correlated with the extent of publication bias. On the other hand, the interaction term of the standard error with the year of publication is positive in both regressions and significant at the 10% level. This can mean that selective reporting has been less problematic in more recent studies collecting abnormal returns effect. There can be two possible reasons: either an improvement of the econometric tool used over the year, or an acknowledgement of the post-acquisition effect over the years: Acquisitions lead to null or negative abnormal returns for the bidder firm on the long run.
Table 5.2: Estimating the mediating factors of publication bias

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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</thead>
<tbody>
<tr>
<td>SE</td>
<td>-1.594***</td>
<td>1.785***</td>
<td>-1.858***</td>
<td>-0.587</td>
<td>-0.739</td>
<td>-0.869</td>
</tr>
<tr>
<td></td>
<td>(0.149)</td>
<td>(0.301)</td>
<td>(0.374)</td>
<td>(0.743)</td>
<td>(0.862)</td>
<td>(0.913)</td>
</tr>
<tr>
<td>SE*Impact</td>
<td>0.0194</td>
<td></td>
<td>-0.0711***</td>
<td>-0.0194</td>
<td></td>
<td>-0.138</td>
</tr>
<tr>
<td></td>
<td>(0.0206)</td>
<td></td>
<td>(0.00327)</td>
<td>(0.0399)</td>
<td></td>
<td>(0.0864)</td>
</tr>
<tr>
<td>SE*Pub.Year</td>
<td>0.0000791</td>
<td>0.000152***</td>
<td></td>
<td>0.0000227</td>
<td>0.000159</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0000627)</td>
<td>(0.0000554)</td>
<td></td>
<td>(0.0000594)</td>
<td>(0.000105)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.145</td>
<td>0.179</td>
<td>0.191</td>
<td>-0.872</td>
<td>-0.758</td>
<td>-0.776</td>
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<tr>
<td></td>
<td>(0.0978)</td>
<td>(0.121)</td>
<td>(0.143)</td>
<td>(0.755)</td>
<td>(0.760)</td>
<td>(0.837)</td>
</tr>
<tr>
<td>Observations</td>
<td>430</td>
<td>451</td>
<td>430</td>
<td>430</td>
<td>451</td>
<td>430</td>
</tr>
</tbody>
</table>

Note: The table shows the results of regression $A_{jt} = A_0 + \beta_0.SE(A_{jt}) + \gamma.SE(A_{jt}).X_t + \epsilon_{jt}$ where $A_{jt}$ is the $j$-th estimate of AR effect reported in study $t$, $SE(A_{jt})$ is the standard error and $X_t$ is either an impact factor of the outlet, in which study $t$ was published, or the year of publication $t$. Specifications (1)-(3) are estimated using OLS with standard errors clustered by study. Specifications (4)-(6) are panel data regressions with fixed effects. Standard errors are reported in parentheses. *, **, *** denote significance at the 10%, 5% and 1% level.
6 Why our AR estimates vary across studies?

6.1 Introducing BMA, the methodology to follow

We have established previously that the asymmetry of the funnel plot can be triggered by the heterogeneity of the AR estimates. We as well witnessed with the help of our histogram and boxplot that there potentially can be heterogeneity amongst our estimates which could lead to bias our results. We will now try to investigate this empirically and try to understand why our AR estimates vary across studies.

We can therefore try to explain these differences and impute them to individual study design characteristics. We are going to apply Bayesian model averaging in order to tackle several issues. Firstly, in order to counter the heterogeneity of the AR effect, we need to improve the regression model from chapter 5:

\[ AR_{jt} = AR_0 + \sum_j \beta_j X_{jt} + u_{jt} \]  \hfill (6.1)

Where AR is our AR effect, \(AR_0\) is a constant, \(\beta\) is a vector of coefficients, \(X_{jt}\) are variables capturing the study characteristics- including the standard-errors- and \(u_{jt}\) is a normal IID error term.
We encounter an obstacle, the matrix of regressors X includes a high number of collected independent variables $X_{jt}$, and we are doubting regarding which subset to use. For our dataset, we have collected 13 different characteristics of the primary studies and their respective models. It could be ineffective to use all of them and we could fail to identify pertinent independent variables. With our 13 variables, we could very well estimate $2^{13}$ variable combinations and build $2^{13}$ different models. Using BMA will allow us to estimate models for all possible combinations of $X_{jt}$ and to calculate a weighted average over all of them. Our aim is to assess the size of each variable’s effect on the AR effect. To briefly sum up how BMA is functioning, it views unknown parameters of the model as random variables and uses Bayes’s theorem and the law of total probability to derive all the results. We will explain the subsequent technique used.

Firtly, we need a dataset D, N explanatory variables and K models, where $K = 2^N$ (each variable is either in or out of the model). Before observing any data, our beliefs about our model $M_k$ are represented by a marginal probability- namely $Pr(M_k)$, which is the prior probability that $M_k$ is the true model. After we observed the data, the posterior probability for $M_k$ is given by:

$$ Pr(M_k|D) = \frac{Pr(D|M_k)Pr(M_k)}{Pr(D)} = \frac{Pr(D|M_k)Pr(M_k)}{\sum_{i=1}^{K} Pr(D|M_i)Pr(M_i)} \quad (6.2) $$

where: $Pr(D \mid M_k) = \int Pr(D \mid \beta_k, M_k)Pr(\beta_k \mid M_k)d\beta_k$

is the integrated likelihood of the model $M_k$, $\beta_k$ is the vector of parameters of model $M_k$, $Pr(\beta_k \mid M_k)$ is the prior density of $\beta_k$ under model $M_k$, and $Pr(D \mid \beta_k, M_k)$ is the likelihood in conventional form.

In (6.2), the conditionnal probability $Pr(M_k \mid D)$ is the likelihood of model $M_k$ occuring given data D and is also called the PMP- Posterior Model Probability. Following Hoeting et all (1999), it represents the degree of belief in $M_k$ having accounted for D.
After having taking into account all possible models $M_k$, the posterior distribution of our effect size $AR$ effect given data $D$ is:

$$Pr(AR|D) = \sum_{k=1}^{K} Pr(AR|M_k, D)Pr(M_k|D)$$  \hspace{1cm} (6.3)

where $M_1,...M_k$ are all the models considered. (6.4) designs the overall posterior distribution and shows an average of the posterior distribution under each of the models considered weighted by their PMP. Averaging across the model space will grant us a better average predictive ability than other single model $M_{jt}$ which will allow us to derive the weighted expected value of $AR$ -known as the posterior mean, as:

$$E[AR|D] = \sum_{k=0}^{K} \hat{AR}_k Pr(M_k|D)$$  \hspace{1cm} (6.4)

where $\hat{AR}_k = E[AR | D, M_k]$, the expected Abnormal Returns effect given data $D$ and model $M_k$. The subsequent posterior variance of the effect size $AR$ is then:

$$Var(AR|D) = \sum_{k=0}^{K}(Var(AR | D, M_k)+\hat{AR}_k^2)Pr(M_k | D) - E[AR | D]^2$$

To determine our BMA model we need to accomplish several steps. Firstly, we will need to specify priors on the model space and on the distribution of the coefficients $\beta$. Secondly we will need to calculate all the integrals specified above and explore the model space. We will further detail our steps in the next section.
6.2 Designing BMA for our AR effect

As mentioned above, BMA is very effective and allows us to reduce the model uncertainty, but its implementation sets several issues. Firstly, our computation in (6.4) could be unattainable due to the high number of models to be weighted. We can tackle this issue by using the MCMC method (Markov Chain Monte Carlo) and approximate (6.4). The Metropolis-Hastings algorithm simulates a Markov Chain whose equilibrium distribution is the desired posterior distribution. Secondly, the integrals in (6.2) could be tricky to compute and require several approximations. However, for linear regression models that we use in our analysis, closed form integrals of marginal likelihood $Pr(D \mid M_k)$ are available. Thirdly, we need to specify the prior distribution over all parameters in all competing models and the prior probability of each models, such a specification can be tough.

Following the work of Zeugner et al (2015), we formulate our prior beliefs on coefficients into a normal distribution with a specified mean variance. In case we are lacking information about them, a prior mean of 0 is a good choice. Their variance is then set thanks to Zellner’s g $(\beta \mid g(0,\sigma^2(\frac{1}{g}X'X)^{-1}))$, which highlights whether or not the coefficients are equal to 0. In our baseline specification, we will apply the UIP (Unit Information Prior) for our g-prior which will set $g = N$ for all models. This further implicates that the prior has roughly the same information as has one observation. Furthermore for our robustness check, we do not apply the UIP for our g-prior but the BRIC which will set $g = max(N,K^2)$.

Following, Hoeting et al (1999) once we obtain beliefs about the importance of a specific model for a model structure, the prior probability on model $M_k$ can be written as:

$$Pr(M_k) = \prod_{j=1}^{p} \pi^{\delta_{kj}} (1 - \pi_j)^{1-\delta_{kj}}$$  (6.5)
where $\pi_j \in [0, 1]$ is the prior probability that $\beta_j \neq 1$ in a regression model and $\delta_{ij}$ is an indicator of whether or not the variable $j$ is included in the model $M_k$. We will consider as a neutral choice the assumption that all models are equally likely when there is not much information regarding the importance of variables and models. In that scenario, we will set the PMP as uniform, all models will be equally likely to be correct.

In order to avoid any multicollinearity, we will set up a correlation matrix for all the study characteristics we will use (Appendix, Figure B1). The color scale of the matrix has two purposes. Blue indicates a total positive correlation and red indicates a total negative correlation. There is a strong negative correlation between AR and SE but we will keep these two in the model. There is as well a strong positive correlation between Cits and Impact. The final version of our regression model (6.1) contains 13 explanatory variables that capture characteristics of the estimate itself and the study that reported it. Before starting to execute the BMA, we carefully weighted the observations by the number of estimates from the same study in order to obtain a similar result to the OLS regression executed in the Chapter 5.

In order to run the BMA program, we selected UIP and uniform priors and ran the model using the BMS package in R Studio. Furthermore, we performed a robustness check (available in the appendix) using alternative priors. The results of our BMA analysis include the model inclusion figure (Fig 6.1) and four statistical measures that we will explain below.

The PIP (Posterior Inclusion Probability) refers to the posterior probability that a specific variable is included in the model. It is the sum of PMPs for all models which include the specific variable. PIP will therefore highlight the importance of the variable in explaining the data (the higher it will be, the more important the variable will be to explain the heterogeneity).

The WPM (Weighted Posterior Mean) obtained with the regression (6.5) refers to the model averaged parameter estimate. It is derived from
the individual model estimates that are weighted by their PMP.

The models where the variable is not incorporated are also included in the average, the subsequent parameter estimate is null.

The WPV (Weighted Posterior Variance) obtained with the regression (6.6) contains the weighted average of the estimated variances of the estimated models and also the weighted variance in estimates of the parameter \( \beta_j \) across different models. To be more precise, eventhough we obtain highly precise estimates in every models, we might obtain some uncertainty about the parameter if those estimates are quite different across the other specifications.

Finally, following Zeugner et al (2015), the Conditional posterior sign stands for the sign certainty and is defined as the posterior probability of a positive coefficient expected value conditional on inclusion.
6.3 Results

The Figure 6.1 presents our results of the BMA analysis in terms of model inclusion of the different independent variables. On the vertical axis, the explanatory variables are ranked according to their PIP from the highest (at the top) to the lowest (at the bottom). Meanwhile, the horizontal axis shows the value of the cumulative PIP. The broader the column is, the more likely the model is. Blank cells mean that the variable concerned is not included in that very model. Colored cells mean that the variable is indeed included in the model. Red cells indicate that the variable has a positive coefficient in the regression, meanwhile blue cells indicate the opposite. Almost half of our variables appear in the best models. The numerical results of the BMA are indicated in the table 6.1, further details and diagnostic plots follow in Appendix C. We disclose more information regarding the PIP, posterior mean, posterior standard deviation and conditional posterior signs for all variables. To better assess the results of the PIP, Jeffreys (1961) provides us a scale to assess the importance of each variable. They consider as weak a PIP between 0.5 and 0.75, they consider as substantial a PIP between 0.75 and 0.95, as strong a PIP between 0.95 and 0.99 and as decisive if the PIP exceeds 0.99.

We classify the variables into categories as in chapter 4. In each cluster, there are study characteristics that will influence our estimates and help to explain the variation among our AR effect. The characteristics linked to the publication selected for the Meta-Analysis do affect our AR effect. The year of publication and the number of citations are variables very significant to explain the variance among our AR estimates. Linked to what we have established previously, the quality of the journal is not correlated with the extent of the heterogeneity with a weak PIP.
However, it is when looking at the specifications of our data that we obtain interesting results. Authors using data from the ISE tend to obtain estimates of the AR effect that are -1.594 smaller on average. This variable has a substantial impact with a PIP of 0.893. However, the other stock exchanges or type of abnormal returns collected really have a small positive impact on the final AR effect. These variables have a weak impact according to their very low PIP. Regarding the characteristics linked to the estimation, we find out that authors using the market model for their estimation report AR estimates smaller by more than -2.50. This variable has a strong impact according to its PIP. OLS estimation brings as well substantial negative impact, meanwhile the other variables have a very low positive impact. Except the MM variable, these others variables are not very significant according to their weak PIP. We can conclude that data coming from the ISE, using the Market Model and estimating abnormal returns using OLS technique lead to significant and negative AR estimates.

Nevertheless, what is striking when looking at these results are the importance of the standard-error terms. They are very decisive (PIP equal to 1). The standard-errors influence our AR estimates and lead to a negative AR effect, estimates are on average -1.259 smaller. This further means that publication bias is present in the reported literature and that the Standard error variable is crucial to explain the variance amongst our AR estimates and why it leads on average authors to report negative estimates. As explained in the previous chapter, some of the studies included in the dataset can differ in precision (data can indeed differ in quality and noise) and studies with high standard errors coefficients tend on average to be involved in more publication bias. This could therefore explain the differences in the reported results and better highlight the conclusion drawn here. We as well kept in mind that the choice of priors affects the results of the BMA, we therefore use alternative priors (namely the random model and the BRIC), the results are enclosed in the appendix. Our results are robust to changes in priors.
Figure 6.1: Bayesian Model Averaging, model inclusion

Notes: The figure depicts the results of the BMA analysis. The dependent variable is the AR effect, i.e., our AR coefficient weighted by the inverse of the number of estimates reported per study. On the vertical axis, the explanatory variables are ranked according to their PIP from the highest (at the top) to the lowest (at the bottom). Meanwhile, the horizontal axis shows the value of the cumulative PIP. The blue color refers to a positive coefficient, red to a negative, and white to the non-inclusion of the specific variable.
Table 6.1: Coefficient estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>PIP</th>
<th>Post mean</th>
<th>Post. std. dev</th>
<th>Cond. pos. sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Error</td>
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<td>-1.259</td>
<td>0.101</td>
<td>0.000</td>
</tr>
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<td><strong>Publication characteristics</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PubYear</td>
<td>0.971</td>
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<td>0.026</td>
<td>0.000</td>
</tr>
<tr>
<td>Impact</td>
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<td>-0.005</td>
<td>0.101</td>
<td>0.095</td>
</tr>
<tr>
<td>Cits</td>
<td>0.974</td>
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<td>0.000</td>
<td>0.000</td>
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<td>ISE</td>
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<td>0.752</td>
<td>0.000</td>
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<td>NYSE</td>
<td>0.065</td>
<td>0.028</td>
<td>0.170</td>
<td>0.985</td>
</tr>
<tr>
<td>CRSP</td>
<td>0.076</td>
<td>-0.025</td>
<td>0.153</td>
<td>0.078</td>
</tr>
<tr>
<td>BHAR</td>
<td>0.059</td>
<td>0.010</td>
<td>0.161</td>
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<td>CAR</td>
<td>0.061</td>
<td>0.004</td>
<td>0.128</td>
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<td><strong>Estimation characteristics</strong></td>
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<td>0.135</td>
<td>0.000</td>
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<td>0.303</td>
<td>-0.304</td>
<td>0.536</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Notes: PIP- Posterior inclusion probability; Post mean- Weighted posterior mean; Post.std.dev- Weighted posterior standard deviation; Cond. pos. sign- Conditional posterior sign.
7 Discussion

7.1 The need for a new framework estimating abnormal returns?

One of the conclusions that we established previously is that corporate acquisitions do create value on average, they do, however research on the topic failed to identify how. There are indeed unidentified moderators and variables that need to be incorporated in the models in order to understand how this value is created and to alleviate the weight of publication bias.

Our meta-analysis indeed established that the weight of the publication bias in the M&A literature leads to undervalued and negative estimates of the long run abnormal returns for acquiring firms. We can identify the reasons of many M&A failures and why it led to negative abnormal returns, for example it could be because of the different corporate cultures, management in place, bad economic conditions, etc. However we cannot explain why we obtain negative abnormal returns whenever we try to estimate those.

The existing empirical research has not clearly identified the variables that impact the post-acquisition performances of firms and needs to be updated in order to fully quantify the impact of M&A. So far what we can acknowledge is that in the M&A landscape, it is far more better to be on the target side.
The shareholders of the target can maximize the value of the deal in case of a friendly acquisitions, propose their terms (rather accept cash than stocks, choose the bidder) and extract a significant positive value out of the deal.

It is true to state that the econometric techniques, data and estimation methods used to quantify the impact of M&A on the AR fail to do so and leads to negative results but there are several more reasons that leads to negative AR.

7.2 M&A often do not have a valid reason and leads to failure.

One of the conclusions that we established throughout this study is that overall, acquisitions do not often have a valid economic reason - e.g. financial motives - and are not aimed to create value for the shareholders of the bidding firm. This appears to be paradoxical since the purpose of the managers is to serve the interests of the shareholders and act on their behalves. This is one of the conclusions established by the agency theorists: desires and goals of both executives and shareholders diverged. In order to align the interests of the managers on the ones of the shareholders, they need to implement financial incentives: Bonuses linked to post-acquisition performances, stock options, private benefits, etc.

It is therefore interesting to witness that on average acquisitions appear to be led by managerial motives and destroy value for shareholders. The M&A literature at the moment is not able to provide a valid reason on why M&A is not a vector of value creation for shareholders. Our view is the following: the motives are not quantitative, but rather qualitative. Acquisitions, on average, are not led based on financial analyses to bring more value but are based on personal desire and hubris in order to increase the managers’ personal interests.

Once an acquisition is realized, leads to divestiture and was completed by an entrenched manager, this latter is not not going to reveal his true motives in order not to get evicted by the board or get repri-
manded.

He could justify this acquisition by financial motives in order to keep his position, whilst his motives could very well be personal (beat his competitors, increase his empire, get more financial compensation and personal interests). We therefore tend to state that there is a big shadow overwhelming this area of research, it is truly difficult to conduct a survey investigating why managers complete acquisitions and why it fails, because they will never reveal their true motives.

What could be interesting for further research is to lead a study with relevant data and incorporate manager motives to lead acquisitions. Are acquisitions led for the stock options promised by the board or by the future benefits the company could make by absorbing its supplier? Expanding the operations in Asia and merging with a competitor will really lead to strengthen the sales and the market shares or will it allow the manager to get further personal benefits and spend more time in this continent? These questions are therefore problematic and need to be answered.

We therefore join the view that King developed in his paper:

“Second, and related to the preceding point, managers are advised to be as explicit as possible about how, why, and where acquisitions can be reasonably expected to strengthen their firms. Vague rationalizations that go no farther than the common ‘synergy’ argument should be viewed with skepticism. If managers cannot explain, in clear and compelling terms, how acquisitions positively serve the interests of their firms, those acquisitions will not be consciously managed to best effect.”

We do not think that M&A are just a game played by entrenched managers in order to gain power but encourage future researchers to incorporate managers views in their models in order to alleviate the strength of the publication bias and shed light on the outcomes of M&A.
Another lead to investigate could be to study whether or not any collaboration between two firms (for example through the use of joint-ventures) could lead to negative abnormal returns. There are indeed a lot of hypothesis to test and a lot of results to discover.
8 Conclusion

8.1 Summary of our study

Throughout this thesis we examined the puzzling relationship between corporate acquisitions and expected stock returns. We have broaden our topic into studying the impact of any mergers and acquisitions on a firm long term abnormal returns. We have defined the expected pattern observed over the years as the following: on the long-run, following an acquisition, the bidding firm will experiment negative abnormal returns. Throughout this study we therefore tried to test if there is an "AR effect" following an acquisition, i.e do firms systematically experiment negative abnormal returns following an M&A?

Our work was therefore to test this hypothesis, try to understand why firms obtain such negative returns and trying to find out how to counter this obstacle. After having properly defined and explained the M&A landscape, one can better acknowledge why a firm might turn into inorganic growth, the benefits are indeed numerous as stated.

Nevertheless, the acquisition process is long and every steps of the M&A lifecycle is crucial in order to combine the two entities. The last step of integration is sources of failure for many firms and must be properly examined. In this fashion, the Acquisition integration model developed by Haspeslagh and Jemison (1991) is determinant. Thanks to their model, firms can better plan their acquisition process and answer to two needs: a need for strategic independence and a need for organizational autonomy.
Nevertheless, although the goal of every M&A is to create value for the shareholders of the acquiring firms, the failure rate following an acquisition goes from 60 to 80%. It is therefore against the common belief that M&A are led by the managers of the acquiring firm to serve the interests of the shareholders and bring significant economic growth. To better investigate this area, the literature review helped us to answer to two fundamental questions: Why firms want to acquire? And, under which conditions M&A destroy or create value.

On the one hand, the acquisition desire is mostly led by four motives: Value creation, managerial self-interest, environmental factors and experiences in previous M&A. On the other hand, M&A can destroy or create value depending on: the method of payment used (Stocks, cash or both), the mode of acquisition (hostile takeover, friendly mergers), the relatedness of the acquisition, the corporate governance of both structures and the relative size of the target. After having acknowledged how authors designed their study by understanding the various ways of estimating abnormal returns- CAR and BHAR- and the models used- mostly the Market Model- it led us to better understand the estimation process in order to build our data set and lead a meta-analysis. Indeed, the authors of these papers can lead the study in one way or another to confirm their initial theory. Authors reporting estimates of long-run abnormal returns can be inclined to under-estimate their estimates reported.

Which can later lead to publication bias and heterogeneity amongst the results. As briefly explained by Martin Paldam, a meta-analysis is a quantitative survey of a literature reporting estimates of the same parameter. In order to lead such a study, we collected 451 estimates of long run abnormal returns from 20 studies. We find some evidence of factors driving our abnormal returns reported to be quasi-null or negative. There is some room for publication bias as demonstrated by our analyses.
We used two techniques to detect possible publication selection bias on the literature: funnel plot and meta-regression techniques.

Firstly, the funnel plot suggests that authors tend to publish quasi-null or negative abnormal returns coefficients in their studies, which is a sign of publication bias and on the other hand, our meta-regression analyses suggest that the selective reporting is not related to the quality of the journal (which is measured by the recursive impact factor) but that it is connected to the publication year of the study: newer studies tend to alleviate the weight of any selective reporting. Furthermore, following the classification of Doucouliagos and Stanley (2013), publication bias is indeed present in our sample, the magnitude of the standard error term concurs to state that there is potential publication bias, which is later confirmed by our heterogeneity regression.

Indeed, our BMA analysis revealed that the standard-error term was the most decisive one and leads to a negative AR effect, estimates are on average -1.259 smaller. This further means that publication bias is present in the reported literature and that the standard error variable is crucial to explain the variance amongst our AR estimates and why it leads on average authors to report negative estimates. We as well check for the robustness of our results by selecting alternative priors to run our BMA analysis. The results are in line with our starting model.

The literature depicting long-run abnormal returns following an acquisition appears to be somehow biased and fails to explain how M&A deals are value-enhancing. Our current meta-analysis somehow failed to demonstrate any positive effect from M&A activity on a firm post-acquisition performance. Although, by employing state of the art techniques, such as BMA (to tackle model uncertainty) and MRA tools (to better spot publication bias), this thesis contributes to shed some light on the literature and could be of great help for future researchers.
8.2 Potential leads for future research on the topic

This could suggest that other motives are under-represented in the underlying theory that aims to elucidate M&A outcomes. If acquisitions are not driven by financial motives, it is not disappointing to witness that they do not lead to any value for the shareholders. One of our verdict is to therefore state that the literature trying to assess the outcomes of M&A deals based on economic indicators (stock returns) fails to do so because M&A are not dictated by economic motives, which later leads to biased results and therefore publication bias. The results of our thesis can concur to confirm this hypothesis.

The literature estimating abnormal returns appears to be heavily flawed and present some publication bias which later leads to predict undervalued results. The results of previous meta-analyses led on the topic tend to draw the same conclusions. We therefore encourage future researchers to incorporate the managerial motives into their models in order to fully elucidate why firms turn to M&A and how it can impact their stock returns. We also think that what can be interesting to study could be any collaboration between two firms and the impact on the stock returns. Assessing the impacts of joint-ventures on the stock returns could be another lead to investigate.
9 Bibliography


Homberg, Rost & Osterloh, 2009: «Do synergies exist in related ac-
quisitions? A meta-analysis of acquisition studies», Review of Managerial Science, vol3(2), pages 75-116


10 Appendix A List of studies used in the Meta-Analysis


11 Appendix B Results of the BMA

Figure 11.1: Correlation of the variables

Note: A description of our variables is available in Table 4.2
Table 11.1: Coefficient estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>PIP</th>
<th>Post mean</th>
<th>Post. std. dev</th>
<th>Cond. pos. sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Error</td>
<td>1.000</td>
<td>-1.259</td>
<td>0.101</td>
<td>0.000</td>
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<td><strong>Publication characteristics</strong></td>
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<td></td>
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<tr>
<td>PubYear</td>
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<td>0.026</td>
<td>0.000</td>
</tr>
<tr>
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<td>-0.005</td>
<td>0.101</td>
<td>0.095</td>
</tr>
<tr>
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<td>0.974</td>
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<td>0.000</td>
<td>0.000</td>
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<td><strong>Data Specifications</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ISE</td>
<td>0.893</td>
<td>-1.594</td>
<td>0.752</td>
<td>0.000</td>
</tr>
<tr>
<td>NYSE</td>
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<td>0.028</td>
<td>0.170</td>
<td>0.985</td>
</tr>
<tr>
<td>CRSP</td>
<td>0.076</td>
<td>-0.025</td>
<td>0.153</td>
<td>0.078</td>
</tr>
<tr>
<td>BHAR</td>
<td>0.059</td>
<td>0.010</td>
<td>0.161</td>
<td>0.520</td>
</tr>
<tr>
<td>CAR</td>
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<td>0.004</td>
<td>0.128</td>
<td>0.777</td>
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<td>0.135</td>
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<tr>
<td>FF</td>
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<td>0.135</td>
<td>0.000</td>
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<tr>
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<td>-0.304</td>
<td>0.536</td>
<td>0.000</td>
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</tbody>
</table>

Notes: PIP- Posterior inclusion probability; Post mean- Weighted posterior mean; Post.std.dev- Weighted posterior standard deviation; Cond. pos. sign- Conditional posterior sign.
## Appendix C Diagnostics of BMA

Table 12.1: Summary of BMA estimation

<table>
<thead>
<tr>
<th>Mean no. regressors</th>
<th>Draws</th>
<th>Burn-ins</th>
<th>Time</th>
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</thead>
<tbody>
<tr>
<td>5.7730</td>
<td>(2^k)</td>
<td>(1^b)</td>
<td>2.69 mins</td>
</tr>
<tr>
<td>No. models visited</td>
<td>Model space (2^k)</td>
<td>% visited</td>
<td>% Top models</td>
</tr>
<tr>
<td>462407</td>
<td>8192</td>
<td>5645</td>
<td>100</td>
</tr>
<tr>
<td>Corr PMP</td>
<td>No. Obs.</td>
<td>451</td>
<td>g-prior</td>
</tr>
<tr>
<td>1.000</td>
<td></td>
<td></td>
<td>UIP</td>
</tr>
<tr>
<td>Shrinkage- Stats</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Av=0.9978</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

|             |\n|-------------|
Figure 12.1: BMA diagnostic plots

Notes: The posterior model size distribution and the model probabilities have been produced by the BMS package with uniform model priors
13 Appendix D Robustness Check

Figure 13.1: Bayesian model averaging, model inclusion

Notes: The figure depicts the results of the BMA analysis. The dependent variable is the AR effect, i.e. our AR coefficient weighted by the inverse of the number of estimates reported per study. On the vertical axis, the explanatory variables are ranked according to their PIP from the highest (at the top) to the lowest (at the bottom). Meanwhile, the horizontal axis shows the value of the cumulative PIP. The blue color refers to a positive coefficient, red to a negative, and white to the non-inclusion of the specific variable. The alternative priors are set to "random" and "BRIC".
## Table 13.1: Coefficient Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>PIP</th>
<th>Post mean</th>
<th>Post. std. dev</th>
<th>Cond. pos. sign</th>
</tr>
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<tbody>
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<td><strong>Standard Error</strong></td>
<td>1.000</td>
<td>-1.290</td>
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<td><strong>Publication characteristics</strong></td>
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<td>-0.006</td>
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<td>Cits</td>
<td>0.831</td>
<td>-0.002</td>
<td>0.001</td>
<td>0.000</td>
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<tr>
<td><strong>Data Specifications</strong></td>
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<td></td>
</tr>
<tr>
<td>ISE</td>
<td>0.731</td>
<td>-1.301</td>
<td>0.916</td>
<td>0.000</td>
</tr>
<tr>
<td>NYSE</td>
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<td>0.022</td>
<td>0.154</td>
<td>0.958</td>
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<td>CRSP</td>
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<td>0.131</td>
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<td>BHAR</td>
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<td>0.526</td>
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<td>CAR</td>
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<td>0.141</td>
<td>0.687</td>
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<tr>
<td><strong>Estimation characteristics</strong></td>
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<tr>
<td>MM</td>
<td>0.979</td>
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<td>0.000</td>
</tr>
<tr>
<td>CAPM</td>
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<td>0.021</td>
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<td>0.920</td>
</tr>
<tr>
<td>FF</td>
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<td>-0.180</td>
<td>0.461</td>
<td>0.000</td>
</tr>
<tr>
<td>OLS</td>
<td>0.247</td>
<td>-0.251</td>
<td>0.506</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Notes: PIP- Posterior inclusion probability; Post mean- Weighted posterior mean; Post.std.dev- Weighted posterior standard deviation; Cond. pos. sign- Conditional posterior sign.