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The Effect of a 'Lock-in' on M&A Performance and Advisor Decisions

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Abstract

Due to the rapid economic development, the magnitude of M&A activity is increasing and so is the influence of large investment banks. A growing research body has investigated whether these so-called high-quality advisors provide superior deal performance. Since there is no consensus if high-quality investors yield higher post-acquisition performance and why acquirers choose specific advisors, this study focuses on whether a previous relationship with a M&A advisor and its reputation affects both the deal outcome and the choice to hire the M&A advisor for acquirers located in Europe. Prior research mainly investigates whether the use of a top-tier advisor affects deal outcome, while this research focuses on the reputation and an associated lock-in of the top 500 financial advisors retrieved from league tables. It is found that a higher ranked advisor does not lead to higher post-acquisition performance while reputation, particularly amongst top-tier investment banks, is an important selection criterion to switch from M&A advisor. Furthermore, this research concludes that a previous relationship with an advisor is not associated with higher or lower acquisition performance. However, a lock-in is an important determinant in switching behavior of an acquirer.

Keywords: Merger & Acquisitions (M&A), Financial advisor, Relationship Banking, Lock-in Reputation, League Tables

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1. Introduction

Merger and acquisitions (M&A) activities bring about significant reallocation of resources within the worldwide economy, this makes M&A transactions one of the primary activities in the corporate finance field. In 2018 alone, more than 50,000 deals were executed, with a total deal value of 3,9 trillion U.S dollars worldwide.[1] Top-tier investment banks advised approximately 90% of these deals, which resulted in advisory fees, with a total value of approximately 30 billion U.S. dollars.[2]

The abovementioned figures indicate the magnitude of the influence of large investment banks in M&As. These banks dominate the deals industry, which strengthens their reputation and leads to the general thought that they provide superior services in capital transactions (Golubov, Petmezas, & Travlos, 2012). This build-up reputation of investment banks motivates corporations to hire these banks for their M&A transaction. In theory, the reputation and expertise of top-tier banks should provide superior deal performance, which is reflected by the high advisory fees (Allen, 1984; Shapiro, 1983). However, existing academic research does not confirm this relationship of quality, reputation and price in the field of M&A advisors. Often, a negative or insignificant relationship is found between high-quality advisors and post-acquisition performance (Bowers & Miller, 1990; Michel, Shaked, & Lee, 1991; Rau, 2000). While other studies find more nuanced or even positive results between top-tier financial advisors and abnormal returns (Bao & Edmans, 2011; Golubov et al., 2012; Servaes & Zenner, 1996). The opposing findings in the literature raise the question why corporations hire top-tier financial advisors in the first place, while they don't necessarily yield better acquisition performance. Bao and Edmans (2011) suggest that past market share is used as a selection criterion rather than deal performance for hiring a financial advisor. The reason they put forward for chasing persistence rather than performance, is a potential lock-in to a M&A advisor. Corporations choose a particular bank as their M&A advisor due to the previous relationship they have with that advisor. Motivated by the contradicting empirical evidence, this paper addresses concerns regarding a potential lock-in to a M&A advisor. It examines the effect of a previous banking relationship on the deal outcome and advisor decisions in M&A deals. Hence, this research will address the following research question:

To what extent does a previous advisor relationship affect the deal outcome and acquirer's decision in choosing a M&A advisor?

The dual nature of this research arises from the fact that there are many conflicting results whether a top-tier M&A advisor yields higher deal performance. It would be a bit shortsighted to just extrapolate results

[1] Source: Institute for Mergers, Acquisitions and Alliances.
[2] Source: Thomson ONE.

whether a lock-in benefits or damages deal outcome and immediately look at the influence of a lock-in on the decision to hire a particular M&A advisor. A lock-in variable is constructed by evaluating the previous relationship with a M&A advisor in loan, equity and bond transactions, based on a sample of 1,127 mergers and acquisitions by European acquirers announced from 2009 to 2018. Furthermore, the reputation of an advisor is taken into account, to evaluate whether higher ranked advisors yield higher deal performance and if a higher ranking increases the probability to choose a particular advisor. Reputation is measured by incorporating the top 500 annual ranking of advisors, retrieved from the annual reviewed financial league tables.

This research extends the existing literature on this topic by focusing on the *determinants* of advisor decisions in M&A deals rather than only looking at *predictors* of future deal performance. Moreover, it provides a more recent overview of a potential-lock effect in M&A deals. Also, previous work is mainly focused on U.S. firms and find only a small significant effect for hiring a M&A advisor with which the corporation has a previous relationship. This study uses a dataset which contains European located acquirers, which could lead to a more significant effect. The reason for this is that Europe is characterized as a more bank-based system, where network and long-term relationships are more important (Levine, 2002). This could imply that it is more likely that corporations in a bank-based system would choose their main bank as M&A advisor, due to the previous relationship with the advisor. Another way this study contributes to existing literature concerns the measurement of advisors' quality. This study not only investigates the use of a top-tier advisor, but it takes a broader stance by evaluating whether reputation in general affects both the deal outcome and the choice of a particular advisor. By incorporating the financial league table annual ranking of the top 500 M&A advisors, this research is able to assess whether reputation in general has an effect on post-acquisition performance and the choice for a particular advisor. Lastly, this study not only investigates what motivates acquirers to switch from their main advisor to another advisor, but it is one of the first studies which examines what characteristics of the current advisor persuades acquirers to switch to this advisor.

The findings of this research draw attention to the credibility and usefulness of financial league tables. It is found that a higher ranked advisor does not lead to higher post-acquisition performance while this ranking, particularly amongst top-tier investment banks, is an important selection criterion to switch from M&A advisor. Furthermore, this research concludes that a previous relationship with an advisor is not associated with higher or lower acquisition performance. Yet, a lock-in is an important determinant in the switching behavior of an acquirer.

These findings could have serious implications for M&A advisory, since acquirers base their advisory decisions on financial league tables. The results of this study might encourage firms to search for other selection criteria rather than the ranking retrieved from financial league tables. Also, the insights of this study might incentivize investment banks to act more in line with their clients, because the results could indicate that investment banks only get their mandates based on previous relationships and reputation rather than based on performance. Moreover, bad advice could damage the reputation of an advisor, leading to better advice and in general, an increase in economic prosperity.

This paper continues by providing an overview of the most noticeable and relevant literature in this research area. Hereafter, four hypotheses will be defined. Chapter 3 will elaborate on the methodological approach and data collection procedure. Chapter 4 will outline the data analysis and elaborate on the results. Lastly, chapter 5 will discuss the results and provide explanations for the found relationships. In addition, it will provide a conclusion and outline the most important contributions, limitations and future research recommendations of this study.

2. Literature Review

The relationship between quality, reputation and price is initially modeled in the research of Allen (1984) and Shapiro (1983). These models are based on competitive market situations where product quality is only observable after the transaction. The product is repeatedly sold by the seller and to signal its quality, a premium arises. This premium serves as compensation for the seller to reimburse the expended resources to build its reputation. While these models describe the relationship between quality, reputation and price in product markets, they can be applied to financial advisors in mergers and acquisitions. Since the quality of the services provided by financial advisors is ex-ante observable and the services are repeatedly sold (Capizzi, Giovannini, & Bonini, 2017; Golubov et al., 2012). Chemmanur and Fulghieri (1994) are the first to examine this relationship for the equity underwriting service provided by investment banks. They find that investment banks with a higher reputation provide better quality services, resulting in higher fees.

A financial advisor is selected by an acquirer or target to provide strategic and technical support throughout the takeover process. This support can consist of valuing the acquisition premium, identifying possible synergies or assisting with the negotiation of the takeover terms (Bowers & Miller, 1990). Financial advisors can reduce information asymmetry and transaction costs between the acquirer and the target, since they have a comparative advantage. The main sources of this comparative advantage are threefold. First, financial advisors experience economies of scale due to specialization. Second, important information on the acquirer or subsidiary can be gathered at lower costs, because of the perceived level of discretion of the financial advisor. Last, financial advisors have reduced search costs due to efficiency (Scholes, Benston, & Smith, 1976; Servaes & Zenner, 1996). Since the management team of a corporation does not make M&A decisions very often and has no experience in such decisions, it reaches out to a financial advisor.

The role of financial advisors within a merger or acquisition process has received a lot of attention in the existing literature. According to the *skilled-advice hypothesis*, a high-quality financial advisor who provides valuable support, should improve the probability that a deal is successful (Bao & Edmans, 2011). For example, an investment bank has knowledge about the industry and the market, which could help select a target that is suitable for the acquirer. However, this is often contradicted in the existing literature. When using prestige and reputation as a measure for quality, Bowers & Miller (1990) find that high-quality advisors are able to identify mergers with higher synergies, but they are not capable of capturing the value of those synergies. Another study shows that a less prestigious investment bank (Drexel Burnham Lamber) has outperformed deals advised by top-tier investment banks, measured in acquirers' cumulative abnormal returns (CARs) (Michel et al., 1991). Rau (2000) uses market share as the quality-measure for financial advisors and finds a negative relationship between the market share of the financial advisor and deal performance. Servaes and Zenner (1996) find more nuanced results: announcement abnormal returns are not affected by top-tier financial advisors, or by financial advisors at all.

These results seem to reject the *skilled-advice hypothesis* and might be more in line with the *passive-execution hypothesis*, which states that investment banks are just dealers who follow orders from the management team of the corporation. Within this view, high-quality financial advisors are characterized as execution houses, which do not add value to the economy (Bao & Edmans, 2011). This could have some serious societal implications for the role of investments banks within the economic field.

In contrast to this view, later studies do find results which confirm that top-tier financial advisors provide higher post-acquisition performance than non-top-tier financial advisors (Bao & Edmans, 2011; Golubov et al., 2012). However, Golubov et al. (2012) use a sample on subsidiary, private and public US acquisitions executed between 1996 and 2009 and only report significant results for public acquisitions. This could be due to the fact that the required set of skills is larger in public acquisitions and that financial advisors want to maintain their reputation, resulting in more effort and higher deal values (Golubov et al., 2012). The sample of Bao and Edmans (2011) contains 15,344 deals executed between 1980 and 2007. They differentiate from previous research by using a fixed-effects model which allows for controlling for time-invariant effects. These fixed effects serve as a proxy for unobservable time-invariant measurements of advisors' quality. Results show significant investment bank fixed effects in acquirer abnormal announcement returns. This means that part of the variation in acquirer abnormal announcement returns is explained by unobservable characteristics of the quality of investment banks. So, by incorporating unobservable quality characteristics of investment banks, this study reports a positive relationship between hiring an investment bank and M&A outcomes. This contradicts the finding of earlier studies, indicating that hiring an investment bank causes better M&A outcomes. These different findings can be explained by the fact that prior research uses market share and reputation as a measure for advisor quality, while the study of Bao and Edmans (2011) use past performance and other unobservable measures for quality. However, the authors do mention an important impasse: the quality of an investment bank (measured in past performance) may be a *predictor* of future deal performance, it might not be a *determinant* that serves as a selection criterion for the decision on a financial advisor by an acquirer. Hence, corporations might not look at the past performance of an investment bank while choosing a M&A advisor, even though it has a positive effect on the deal performance. Instead, Bao and Edmans (2011) report high correlations between mandate awards and past market share of an investment bank, indicating that corporations use past market share as selection criterion rather than past performance. Although past market share predicts future deal performance negatively, this could indicate that clients chase persistence, rather than performance. The question raises why clients select their advisor based on their market share rather than high past deal performance. One reason the authors put forward is a potential lock-in to a M&A advisor. A client could use a particular bank as a M&A advisor due to the other services the bank provides.

The aforementioned studies all look at the effect of quality of a M&A advisor on the *deal performance*, measured in cumulative abnormal returns. To study a potential lock-in effect, the determinants of the corporations' *decision* on choosing a M&A advisor need to be examined. Therefore, the dependent variable becomes the choice of hiring an investment bank instead of deal performance. For instance, Yasuda (2005) investigates lock-in effects in securities underwriting processes. He finds that the main determinant for the selection of an investment bank for securities underwriting is the prior lending- and underwriting relationship with the bank. Past leading underwriters are selected as future underwriters (Ljungqvist, Marston, & Wilhelm, 2006). This lock-in stems from two reasons. First, the lock-in to a past underwriter arises because of the creation of an information monopoly for the investment bank. This information monopoly is developed by the previous relationship with the bank, cooperating with another bank would require too much time and effort. Second, clients are afraid that sharing their investment banks results in detrimental spillovers to market rivals (Asker & Ljungqvist, 2010). Bao & Edmans (2011) have examined the potential effect of lock-ins in choosing an advisor in mergers and acquisitions. They conclude that clients use different advisors for their borrowing and underwriting decisions than for their M&A decisions. So, they do not find proof for a potential lock-in. However, they did not formally test it, only looked at acquirer advisor decisions and only incorporated deals until 2007. An earlier study, executed by Allen et al. (2004) find that there are increased abnormal returns when a target firm chooses their bank with which they have an existing lending relationship. In addition, they find evidence that acquirers utilize prior bank lending relationships in choosing their M&A advisor. The opposing findings in the literature make it interesting to investigate whether lock-ins contribute to the fact that clients chase persistence rather than performance.

Previous research on advisors' choice in M&A deals has mainly focused on factors which influence the decision in choosing a financial advisor and their effects on the deal outcome. However, incorporating the factor of a potential lock-in (e.g. previous banking relationship with the M&A advisor) on both the choice for a financial advisor and the respective deal outcome has received only little attention in prior research.

Allen et al. (2004) are the first ones who investigate a potential lock-in effect to a M&A advisor. They examine the effect of a previous banking relationship on the respective deal outcome, rather than the choice for a financial advisor. They examine the role of commercial and investment banks on abnormal returns using a sample involving U.S. target firms over the period from 1995 until 2000. As mentioned earlier, they find increased abnormal returns for targets but not for acquirers when using their main bank as M&A advisor. Forte et al. (2010) analyze the determinants of the target's choice for a M&A advisor and their influence on deal outcomes, looking at European M&A deals during 1994 until 2003. They find that the choice for a financial advisor is influenced by: (1) the intensity of the former relationship with the bank/advisor, (2) the acquirer's advisor reputation, and (3) the deal complexity. They also examine abnormal returns of the target and find that the deal outcome increases when the previous relationship with the advisor is stronger. A more recent study investigated whether the previous relationships with the acquirers' advisor affects the choice to switch from M&A advisors in the current M&A transaction (Francis, Hasan, & Sun, 2014). The sample focuses on U.S. acquirers that conducted an acquisition or merger between 1990 and 2003. The results show that a previous banking relationship has a significant but small effect on the acquirer's choice to choose a particular M&A advisor. They find that acquirers without M&A experience are more likely to choose their financial advisor for related services also for M&A advice in comparison with acquirers with M&A experience.

When reviewing the existing literature on hiring a M&A advisor, there are opposing findings whether the quality of a M&A advisor positively or negatively influences the deal outcome. This might be caused by the various possible measurements of the investment banks' quality. The resulting ambiguous prior findings gave rise to the following first hypothesis:

Hypothesis 1: *There is no association between the use of a higher ranked M&A advisor and the takeover acquirer announcement returns.*

One implication regarding the literature is that large investment banks do not necessarily yield higher deal performance. The question remains why corporations still choose those banks as their M&A advisor. One reason existing literature puts forward is the effect of a potential lock-in on the decision in hiring a M&A advisor. Only little attention has been paid to the influence of a previous relationship with an advisor on the *decision* about a M&A advisor and the respective *deal outcome*. Since there is no consensus whether a potential-lock in benefits or damages the *deal outcome*, this will be investigated first. Accordingly, the second hypothesis is formulated as follows:

Hypothesis 2*: There is a negative association between a previous relationship with a M&A advisor and the takeover acquirer announcement returns.*

Hereafter, *the decision* on choosing a particular M&A advisor will be investigated. First, it will be examined whether the reputation of a financial advisor influences the choice to hire an advisor. This is examined first, since there is no concensus whether the ranking of an advisor is a determinant to choose the specific advisor. Hereafter, the previous relationship and its effect on hiring that advisor will be examined. Therefore, the third and fourth hypotheses are formulated as follows:

Hypothesis 3: *There is a positive association between the use of a higher ranked M&A advisor and hiring the advisor for a M&A transaction.*

Hypothesis 4: *There is a positive association between a previous relationship with an advisor and hiring the advisor for a M&A transaction.*

Previous research on the decision on hiring a M&A advisor based on a lock-in is directed towards firms located in the U.S. and find only a significant effect for target firms (L. Allen et al., 2004) or no significant effect at all (Francis et al., 2014). The study of Forte, Iannota and Navone (2010) does focus on European M&A transactions, but they only incorporated target firms in their research. Therefore, with focusing on acquirers located in Europe, this study attempts to fill the research gap in the existing literature regarding the effect of a potential lock-in on both the deal outcome and the decision on M&A advisors.

3. Research Method

This chapter will explain the methodology of the study. Section 3.1 describes the data collection procedure, the sample and its criteria. Hereafter, section 3.2, 3.3 and 3,4 will outline the dependent variables, the independent variables and the control variables, respectively. Lastly, section 3.5 will specify the used analysis.

3.1. Data sample description

To provide an answer to the research question, a quantitative research method will be adopted. Data on mergers & acquisitions, loans, equity- and bond issuances will be retrieved from Thomson ONE. This database provides integrated access to a few other financial databases such as *Thomson ONE Financial Merger & Acquisition database* and *Securities Data Company (SDC)*. Thomson ONE is the most comprehensive M&A database, since it covers more deals in comparison to other financial databases (Ma, Pagan, & Chu, 2009). Thomson ONE collects data on M&A deals by using various sources, such as annual statistical reports of multiple international trade associations or filings at international supervisors, such as the Securities and Exchange Commission. In this way, a lot of deals are captured, ranging from multi-billion dollar deals to small, undisclosed transactions (Brewster, 2016). Thomson ONE provides information on deal-specific information, acquirers profile (e.g. size or industry) and advisor information. Furthermore, Thomson ONE provides information on loans, equity- and bond issuances by the acquirer and its book runner. This will be used to identify the relationship between the acquirer and its M&A advisor.

Additionally, M&A advisors' specific-information is derived from the Eikon Database. This database provides annual league tables on the performance of M&A advisors. The annual derived league tables reflect the top 500 of financial advisors on acquirer M&A deals in Europe. It contains information on the ranking of the advisor, its market share and the number of deals it has executed in the specific year. In addition, data on the stock performance of the acquirers is also retrieved from Eikon.

The initial sample will include all EU-located acquirers which conducted a merger or acquisition between January 1, 2009 and December 31, 2018, where there is information available about the acquirer and its financial advisor. The rationale for this specific period arises to exclude the sixth merger wave from 2003 until 2008. During this period, there was a rebirth of leverage, which resulted in very large transactions due to very cheap credit. These large transaction values are a consequence of the ease with which firms could get money for their acquisitions. Excessive lending and the phenomenon of mortgage-backed securities resulted in overpayment for targets (DePamphilis, 2009). This could bias the results. Therefore, this period is excluded in the initial sample, to assure data availability, December 31, 2018 is chosen as the end of the data period.

The initial M&A sample focuses on acquiring companies located in Europe and listed on a stock exchange, to ensure data availability on stock returns. The percentage of shares owned after the transaction is larger than 50%, because this research focuses on deals that reflect a transfer of control (Faccio, McConnell, & Stoli, 2006). Acquiring companies which are characterized as a financial company (SIC codes 6000 - 6999) are not included in the sample. Exclusion of companies in a finance related industry should prevent biased results, since these companies have a different regulatory framework, capital structure and operating activities (Bliss & Rosen, 2001; Vafeas & Theodorou, 1998). When these financial firms are included, no conclusions can be made regarding a general effect, since these institutions operate differently in comparison with the average firm. These institutions have different incentives to engage in a merger than other firms. In addition, this study examines advisory relationships between acquirers and financial firms, when the acquirer would operate in the financial industry too, the observed relationship between the acquirer and the advisor might be biased. Furthermore, mergers in these industries are often initiated by the local government to prevent the bankruptcy of a company (Dymski, 2002). Lastly, uncompleted transactions and self-tender offers are excluded from the sample. The latter could bias the results, since it is a defense action against a hostile takeover, resulting in more expensive target shares (Lie, 2002).

Information on bond- and equity issuances and loan agreements of the acquirer five years prior to the M&A announcement is retrieved from Thomson One, which is used to evaluate a potential lock-in (Francis et al., 2014). Since the advisor codes retrieved from the deals data sample and from the bond-, equity and loan issuances are slightly different, these codes are manually checked and combined into one single code if they belong to the same advisor or book runner. For instance, '*ING-ADVICE* and '*ING-BANK'* are both adjusted to '*ING*.' In this way, the existence of a previous relationship with the advisor can be measured more accurately. This is in line with the methodology of Chang et al. (2016).

It occurs that a deal is assisted by more than one advisor. In this case, only the lead advisor is taken into account to evaluate a lock-in effect. Also, often multiple book runners accompany a firm with their bond, equity or loan issuance. In these cases, only the first book runner is considered, since this is the lead book runner of the issuance. One could argue that this measurement of a potential lock-in is not complete since it does not incorporate all book runners related to the loan or security issuance. On the other hand, since some loan agreements or security issuance were issued by at least 30 book runners, a match between the M&A advisor and book runner can be easily found. Besides, Thomson One does not specify which value of the loan or security issuance can be attributed to which book runner. Taking into account the previous two arguments, incorporating all book runners to measure the previous relationship intensity would cause a lock-in to be easily found. This could also bias the results. Therefore, measuring a lock-in to a M&A advisor by only considering the first book runner of a loan agreement or security issuance is justified. This argument also holds for only taking into account the lead M&A advisor. Some transactions are advised by seven advisors. By incorporating all these advisors into the analysis, a lock-in would also be found too easily, which makes it complicated to draw a conclusion.

The abovementioned search criteria result in an initial sample of 3.074 deals. Excluded from the sample are deals with advisors which do not have a license to underwrite securities or issue loans. This leaves 1.768 observations. When excluding observations which do not have data on stock returns, a sample of 1.352 observations is left.

3.2. Dependent variables

To practically examine whether the ranking of an advisor and a potential lock-in affects the *deal outcome* and the acquirer's *choice* of a M&A advisor, two similar regressions will be executed, where only the dependent variable will be different.

Analysis 1: acquirer cumulative abnormal returns

To model whether the ranking of an advisor and a potential lock-in affects the deal outcome, the deal performance is measured by calculating the cumulative abnormal return (henceforth CAR) of the shares of the acquirer around the announcement date of the deal. It is an established measure in the academic literature to quantify the post-acquisition performance around a transaction announcement (Binder, 1998). In comparison with other measures of performance, such as accounting-based returns, CAR truly reflects the performance of the firm. CARs are based on stock prices, which should reflect the accurate value of the firm, in theory. Accounting profits can be manipulated by managers (Benston, 1982), whereas stock prices are assumed to incorporate all available information based on the discounted value of the company's future cash flows (McWilliams & Siegel, 1997). To capture a market reaction accurately, there will be focused on the announcement date of the M&A transaction instead of the effective date. Because, focusing on the latter would result in already updated market expectations, reflected in the stock prices (MacKinlay, 1997).

The CARs are calculated by using the following procedure. Initially, the average return of the acquiring company is calculated and compared with the market return around the announcement date. To calculate the average return, an estimation window from -250 to -5 trading days preceding the announcement date will be used. It is assumed that the estimation window is not affected by the event itself, so it ends a few days prior to the event (McWilliams & Siegel, 1997). When the estimation window would be extended, the average return might be better in reflecting the parallel movement of the company's stock and the market return. On the other hand, a longer estimation window might bias the expected average return since it could also capture other events which affect the average return. The abovementioned estimation window is in line with previous empirical research (Forte et al., 2010; Francis et al., 2014).

The average rate of return on the stock price of a company *i* on day *t* is given by the market model. This is calculated by using the following equation (Kwan, 1984):

$$R_{it} = \propto_i + \beta_i R_{mt} + \varepsilon_{it} \quad (1)$$

Where

R_{it} = rate of return on the stock price of the company *i* on day *t*.

$\propto_i$ = the intercept term, average return on stock *i* when there is no market return.

β_i = stock *i* systematic risk, reflects the co-movement of the stock with its market.

R_{mt} = rate of return of the market index on day *t*.

ε_{it} = the error term, which is expected to be 0.

Thereafter, abnormal returns of the stock prices, which lie in the event window, are calculated. The event window is the time interval where the M&A announcement will take place. Choosing an appropriate event window is crucial for capturing the effect of a M&A announcement (McWilliams & Siegel, 1997). Furthermore, the time interval has consequences for the interpretation of the relationship between the independent variables and deal performance. A too short event window might not capture all announcement effects regarding the event. This could be due to information leakage. This particularly holds in emerging markets, where capital markets are less efficient and it takes time for stock prices to reflect all available information (Ryngaert & Netter, 1990). On the other hand, a too long event window might also capture confounding effects of other events affecting the performance of a company. For instance, the declaration of dividends or the announcement of a new product line. In addition, empirical evidence has shown that a longer event window decreases the likelihood of capturing a significant effect of an event (Dann, Mayers, & Raab, 1977; Ryngaert & Netter, 1990). This is due to the fact that a too long event window decreases the power of test statistic Z_t (Brown & Warner, 1985). When considering the arguments mentioned above and relying on the assumption that European stock markets are efficient, an event window of -1 to +1 trading days around the announcement day is used.[3] The chosen event window is in accordance with prior research regarding advisor lock-ins on deal performance (Bao & Edmans, 2011; Chang et al., 2016).

The estimates of daily abnormal returns (AR_{it}) on the stock price of the company *i* is calculated by using the following equation:

$$AR_{it} = R_{it} - (a_i + b_i R_{mt}) \quad (2)$$

[3] A robustness check on a longer event period (-5 till +5) is incorporated to be certain that the observed relationship is no result of the selected event period. In this way post-event drifts and possible information leakage can be captured, since it might take some time for stock prices to incorporate and reflect all available information regarding the M&A announcement.

Where

a_i ; b_i = parameter estimates of the ordinary least squares (OLS) generated from the regression R_{it} on R_{mt} over the 245-trading days estimation period.

AR_{it} = returns of the company *i* after subtracting the expected 'normal' return from the actual return.

Finally, the cumulative abnormal return variable is derived from the daily abnormal returns. Since investors might anticipate differently per day during the event window, CAR is better able to reflect the market reaction in comparison with daily abnormal returns (Brown & Warner, 1985). The daily abnormal returns will be cumulated over the event period, to determine the cumulative abnormal return (CAR) for each company i.

$$CAR_{i,t_1,t_2} = \sum_{t=t_1}^{t_2} AR_{it} \quad (3)$$

Where

$CAR_{i,t1,t2}$ = cumulative abnormal return for each company *i* over the event window.

t_1 = -1 trading days prior to the announcement date.

t_2 = +1 trading days after the announcement date.

CAR will serve as a proxy for deal performance, indicating the market sentiments of investors regarding the M&A transaction. A positive CAR indicates that shareholders have updated their beliefs regarding the M&A transaction and expect higher company returns due to the acquisition, this can be interpreted as positive deal performance.

Analysis 2: acquirer switching behavior

To investigate whether a potential lock-in affects the acquirer's *choice* of a M&A advisor, a dummy variable will be used as dependent variable. The dummy variable equal to 1 if the acquirer switches from their main M&A advisor to another advisor in the current M&A deal. The dummy variable is equal to 0 when the acquirer retains their main M&A advisor in the current M&A transaction. This is in line with the methodology in previous studies (Chang et al., 2016; Francis et al., 2014). In this way, the likelihood that the acquirer hires its main advisor for the current deal is investigated. The measurement of this variable has two important implications. First, when the main advisor of an acquirer cannot be determined (e.g. the acquirer has another M&A advisor every time it engaged in a M&A transaction) the dummy variable is equal to 1, since they switched. Second, when the acquirer only executed one deal in the observed period, the dummy variable is equal to 0. These implications can bias the results. Therefore, an additional regression is performed where merely firms are incorporated which (1) occur in the dataset more than once and (2) the main advisor can be determined.

3.3. Independent variables

Previous relationship with the M&A advisor

One of the main independent variables is the previous relationship with the advisor, which could serve as a proxy for a potential lock-in. The literature shows various methods to measure this variable. Allen et al. (2004) define the previous credit/lending relationship with the M&A advisor with four different dummy variables, which measure the bank's previous relationships with the target or acquirer. Francis et al. (2014) also use a dummy variable whether acquirers keep their previous equity underwriter as M&A advisor. In addition, they divide their sample into subsamples and rank the samples based on the strength of the relationship with the advisor. Forte et al. (2010) capture this variable by using a ratio of two values, which measures the intensity of the target's previous relationship with the bank. The dollar value of all transactions where the given bank was the lead manager or advisor is divided by the total dollar value transactions completed by the target over the last five year. A ratio of 0 indicates no previous relationship with the advisor, and a ratio of 1 indicates the strongest possible relationship with the advisor.

This paper will both use the ratio-approach of Forte et al. (2010) and a dummy-approach to measure the lock-in effect[4], to provide a more comprehensive measurement of the previous relationship with the advisor.

Following a modified procedure of Forte et al. (2010) the intensity of the acquirer's previous relationship with the advisor is derived from the following ratio:

$$D_i^q = \frac{\sum_{j=1}^{i-1} value_J^D * Q_j}{\sum_{j=1}^{i-1} value_J^D} \quad (4)$$

Where

D_i^q = is the intensity of the previous relationship between the acquirer i and advisor q at the time of the deal.[5] The intensity is the dollar value of the total transactions where the particular M&A advisor was the lead book runner, divided by the total dollar value of loan, bond and equity transactions completed by the acquirer over the last five years.

Q_j = is an indicator which equals 1 when the lead book runner of the loan-, equity-, or bond issuance is the lead advisor of the M&A deal.

[4] This will be incorporated by means of a robustness check.

[5] Substracted are loan agreements and securities issuances which are used to finance the acquisition (Forte et al., 2010; Francis et al., 2014).

The procedure is modified, since Forte et al. (2010) establish this intensity variable for every bank a firm had a loan, bond or equity transaction with. Hereafter they assess the main bank of each firm and examine the potential lock-in to choose this M&A advisor. The starting point of this research is the advisor of an acquirer, instead of evaluating all banks with whom the acquirer had a previous relationship with. From here, the previous relationship intensity with that advisor is established by looking at all loan, bond and equity transactions.

In addition to the ratio variable, a dummy variable will be created whether the acquirer had some sort of relationship with its advisor in the previous five years before the deal announcement date. What is striking about the existing literature is that they all only look at a time interval of five years before the transaction deal when measuring the previous relationship with an advisor (Forte et al., 2010; Francis et al., 2014). Allen et al. (2004) use a broader time interval to define a previous relationship, they investigate whether the acquirer has any previous relationship with its advisor at all. Since a time interval of five years could be a bit too short to make assumptions about a previous relationship, a robustness check is executed whether the acquirer had a prior involvement with its M&A advisor from the year 2000 until the announcement date of the deal.[6]

Reputation of the advisor

The other main independent variable is advisor reputation (*REP_AV*). Chang et al. (2016) use the advisor's market share as a proxy for banks' reputation. Allen et al. (2004) incorporate dummy variables whether a bank is a top-tier investment bank, mid-tier investment bank or commercial bank to capture the reputation of the advisor. Since this last measurement can be retrieved from league tables, which reflects the market sentiment, it would serve as a better measurement of the overall reputation of an advisor. These financial league tables are based on several criteria, such as deal volume, deal value or market share (Ismail, 2010). Since league tables provide a rank of the first 500 M&A advisors within a particular year, this variable is used to assess advisor' reputation. The reputation variable is measured yearly, which is considered to be a better approach, then incorporating dummy variables such as Allen et al. (2004). In this way, it really reflects the market sentiments within a particular year about an advisor rather than just keeping the same dummy variable to assess the reputation of an advisor. As stated in hypotheses 1 and 3, a positive relationship is expected between the ranking of a financial advisor and the probability of being chosen. However, there is no consensus whether a higher ranked advisor leads to higher deal outcomes.

[6] This specific year is chosen due to data availability.

3.4. Control variables

In accordance with prior research (Bao & Edmans, 2011; Forte et al., 2010; Francis et al., 2014) several control variables are incorporated to account for potential alternative variables that influence deal outcome and the choice to switch to another M&A advisor. These controls can be divided into four broad categories: (1) control variables which measure the characteristics of the advisors, (2) control variables which measure the characteristics of the acquirer and target, (3) deal-specific controls and (4) country-specific controls. The remaining part of this section will discuss the different control variables and their expected outcome on both the cumulative abnormal returns and the decision whether an acquirer switches to another M&A advisor.

Advisor controls

To really isolate the lock-in effect, one must control for advisor experience (*EXP_AV*). This can be defined as the number of deals executed by the advisor annually. Literature shows that the expertise of an advisor does not lead to value creation for acquiring firms, but that it is an important determinant for the acquirers' advisor choice (Chang et al., 2016).

Furthermore, advisory fees (*FEES_AV*) and the market share of an advisor (*MASH_AV*) within a particular year are incorporated to control for the ability to accept mandates. It is expected that advisory fees have a positive impact on the deal outcome, since advisory fees tend to get larger when the size of an acquirer increases, which is accompanied by greater abnormal returns (Hunter & Jagtiani, 2003). It is expected that advisory fees have a negative effect on choosing a particular M&A advisor. Since market share is also a proxy of advisors quality, it is expected that it does not lead to value creation for acquiring firms in terms of performance (Rau, 2000), but that it is a selection criterion to choose an advisor.

Financial Advisors which are not in the top 500 league tables will get a value of 0 on advisor experience (*EXP_AV*) and market share (*MASH_AV*). It will get a ranking of 500 for advisor reputation (*REP_AV*). This applies to a total of 57 observations.[7]

Acquirer & target controls

The more experience an acquirer has with M&A transaction, the less it has to rely on external advice for its transaction. On the other hand, the larger the acquirer, the more difficult the valuation of a transaction might be, which might result in more need for external advice. Therefore, there needs to be controlled for the relative size of the acquirer and its experience with acquisitions. The latter (*EXP_AQ*) can be captured by the number of deals executed by the acquirer before the current transaction (Francis et al., 2014). It is expected that the more expertise an acquirer has in M&A deals, the higher its abnormal return. Also, target

[7] A robustness check is executed to test whether the results still hold when these modified observations are left out. The results are outlined in table 17 and 21 in Appendix I and J, respectively.

experience is included (*EXP_TG*), since it is expected that prior experience of the target firms also lead to higher deal performance, since it improves the selection process and integration of both firms (Aktas, De Bodt, & Roll, 2011). It is expected that the experience of the acquirer (*EXP_AQ*) increases the likelihood of switching to another advisor, since the acquirer gathers more knowledge about the acquisition process and therefore becomes more demanding. The effect of target experience on the likelihood of switching to another advisor is ambiguous.

Furthermore, the size of the acquirer (*SIZE_AQ*) is measured as the value of the acquirers' total assets (Bao & Edmans, 2011). One expects a negative relationship between the size of an acquirer and deal performance, due to worse alignment with shareholders' interests in a larger company and managerial hubris, what causes overpayment of target firms (Moeller, Schlingemann, & Stulz, 2004). The effect of the acquirer's size on switching to another advisor is expected to be positive, since a larger acquirer might be more demanding regarding its advisor.

Deal-specific controls

As stated in the literature overview, a M&A advisor is selected to reduce the information asymmetry between the acquirer and the target when a transaction tends to be more complex. Song et al. (2013) show that acquirers tend to choose a small or boutique financial advisor when the deal is more complex. It is argued that boutique financial advisors provide better advice than their large competitors due to their great understanding of the industry of their client. A boutique financial advisor is defined as an advisor specialized in a particular industry and does not offer a full range of financial services (e.g. lending, underwriting or commercial banking) (Loyeung, 2018). Choosing a small financial firm as advisor is beneficial for the acquirer because of the lower deal premiums. To incorporate the probability of choosing an boutique financial advisor when the deal tends to be more complex, there will be controlled for deal complexity and information asymmetry by incorporating various measures which could serve as proxies to measure the complexity of the deal and its resulting information asymmetry (Loyeung, 2018; Song et al., 2013).

The first measure to capture deal complexity is *DEALV*, which is the value of the transaction measured in million dollars. A negative relationship with deal performance is expected, since a high transaction value often reflects a high deal premium resulting in lower cumulative abnormal returns for the acquirer (Loyeung, 2018; Moeller et al., 2004). The effect of transaction value and switching to a particular M&A advisor is expected to be positive, since a higher transaction size comes with higher fees, which might stimulate acquirers to look for other advisors.

Furthermore, the payment method also reflects the complexity of the deal, which has implications for the performance of the acquirer. The acquisition can be either equity, debt or cash financed. An equity financed takeover often triggers low acquirer shareholders return since it signals that the shares of the acquirer are overpriced (Martynova & Renneboog, 2009). A takeover which is financed with internally generated funds causes higher abnormal returns in comparison with equity financed acquisitions, due to undervaluation of the assets (Yook, 2003). Therefore, the variable *CASH* is incorporated to reflect the percentage of used cash to finance the acquisition. It is expected that a higher percentage of cash used to finance the acquisition, yields higher deal performance. The effect of *CASH* and choosing a particular M&A advisor is ambiguous.

Another variable to measure deal complexity is the percentage of shares owned after the transaction (*PERC*). A higher percentage indicates that there is more at stake for both the acquirer and the target, which results in more control issues and approval procedures. It is expected that this causes lower deal performance and stimulates switching to another advisor.

The number of acquirer advisors (*NUM_AQAV*) and whether multiple bidders are involved in the transaction (*NUMB*) are also included to measure the complexity of a deal (Forte et al., 2010). For both variables, a negative relation with deal performance is expected. This research is the first to include (*NUM_AQAV*). This variable is included since only the lead M&A advisors are taken into account in this research and yet to be able to deal with the existence of multiple advisors. It is expected that both variables might increase the likelihood of switching to another M&A advisor, since the deal tends to be more complex and firms might switch from advisor due to their experienced pressure.

Lastly, the attitude of a takeover is taken into account by incorporating a dummy variable with a value of 1 when the takeover is friendly and 0 otherwise (*ATT*). Positive acquirer announcement returns are expected when the transaction is characterized as friendly, since these takeovers reduce information asymmetry because two parties are willing to cooperate (Goergen & Renneboog, 2004). The effect of a friendly takeover is expected to decrease the probability that an acquirer switches to another advisor, since the deal is less complex than other type of deals.

Also, as outlined in the introduction, a lock-in is more likely when information asymmetry is high. Therefore, there needs to be controlled for information asymmetry. Literature shows various ways to measure this variable: whether the acquirer operates in the same SIC-industry (*SICSAME*) as the target, or whether it is a cross-border transaction (*CRB*). Both will increase the unavailability of information (Forte et al., 2010). *SICSAME* is equal to 1 when the acquirer and the target operate in the same industry. A positive relationship between *SICSAME* and deal performance is expected, since it reduces information asymmetry. *CRB* is equal to 1 when the transaction is characterized as a cross-border transaction and therefore, a negative relationship between *CRB* and deal performance is expected. Since both variables measure deal complexity and information asymmetry, it is expected that when the industries of the acquirer and target are related (*SICSAME*), this negatively influences switching to another advisor. The opposite holds when the transaction is characterized as a cross-border deal.

Country & year specific controls

Lastly, there needs to be controlled for time-specific and country-specific controls, to assure that the obtained results are no consequence of market sentiments and institutional differences among countries. This can be done by incorporating the dummy variables for the years 2009 - 2018 and incorporating specific dummy variables for the different countries. This is inline with previous research (Forte et al., 2010; Song et al., 2013).

3.5. Models

Model 1: acquirer cumulative abnormal returns

The relationship between a previous advisor relationship and the performance of a M&A transaction is examined by using an ordinary least squares regression (OLS). The sample is checked whether it satisfies the fundamental assumptions of the OLS analysis. Accordingly, it is first examined whether the sample contains outliers or influential points. Outliers are detected by looking at the partial plots and examined by performing studentized tests[8] (Lehmann, 2012). It detects outliers by dividing the residual of an estimate by its standard deviation. Individual observations which have a disproportional influence on the regression coefficients are considered to be influential cases and removed from the dataset. This is tested by using DfFit[9] and Cook's Distance[10] (Berry & Feldman, 1985). Both measures indicate the difference between the estimated coefficients with and without the potential influential points.

Subsequently, the variables are checked for being normally distributed, to obtain non-biased results. This is tested graphically by looking at the combination of the histogram and a density plot of the variable to assess whether they are normally distributed. Furthermore, a numerical test is used to check if the variables deviate from a normal distribution. When a variable is positively skewed, this indicates that the tail at the right side of the distribution is longer or fatter than the left sight. When a variable has a high kurtosis, this indicates that the central peak of the distribution is very high and sharp. This implies that a relatively large part of the variance is a consequence of rare extreme values (Groeneveld & Meeden, 1984). The variables *SIZE_AQ*, *DEALV* and *FEES* are not in the acceptable range for kurtosis and skewness[11], this is corrected by taking the natural logarithm of these variables.

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[8] An observation is considered to be an outlier when the internally studentized residual is larger than its critical value of 2.58, in absolute terms (Lehmann, 2012).

[9] Change in the estimated value for a point, which is obtained when the particular point is left out of the analysis. An observation is considered to be influential when its DFFITS is larger than the critical value of $DfFit > 2 * \sqrt{\left(\frac{p}{n}\right)}$, where p is equal to the number of parameters and *n* is equal to the total observations in the model (Berry & Feldman, 1985).

[10] Measures the effect on the regression output when erasing a given observation. An observation is considered to be influential when its Cook's D is larger than the critical value of $D > \frac{4}{n}$, where *n* is equal to the total observations in the model (Berry & Feldman, 1985).

[11] The acceptable value for kurtosis is approximately 3. The acceptable value for skewness is approximately 0. (Groeneveld & Meeden, 1984).

Furthermore, the residuals are tested on homoscedasticity. This is done graphically and statistically. First, the error terms are plotted against the fitted values (predicted responses). Hereafter, a Breusch-Pagan test is executed. This test shows a significant p-value (p = 0.0000), indicating that the data experiences heteroscedasticity. This indicates that the variation in the residuals is not constant and that standard errors of the parameters could be biased (Berry & Feldman, 1985). Due to heteroscedasticity, (clustered) robust standard errors are used in the analyses. The Breusch-Pagan test is executed for each regression, but only the result for the first regression is listed in table 4 in Appendix B, since each test result implied that the data suffers from heteroscedasticity.

The unit of analysis in this study is completed M&A deals by corporations who are accompanied by a M&A advisor. The dataset contains a sample of firms of which some have engaged in multiple M&A transactions during the observation period. Hence, some firms are represented multiple times in the sample, due to various M&A transactions. As a consequence, the data comprises an unbalanced panel, due to varying M&A transactions per firm. When the data is addressed as pooled cross-sectional data, the within-firm correlation of the residuals is being ignored. Accordingly, each observation is treated as an individual, independent observation. On the other hand, a fixed or random effects model could account for these within-firm correlations (Petersen, 2009). However, the dataset is characterized as an unbalanced panel. Meaning that the firms in the sample are not followed over time and only included in the sample when they engaged in a M&A transaction. Therefore, clustered robust standard errors are used to account for correlation within the firm. The advantage of using clustered robust standard errors in comparison with using a similar random effects approach is that it allows for producing consistent estimates while taking into account multiple possible correlations (due to the varying occurrence of firms in the dataset). It accounts for residual dependence created by the repeated presence of firms in the dataset (Cameron & Trivedi, 2009). Furthermore, it deals with heteroscedasticity in a better way than robust standard errors, since robust standard errors do not account for within-cluster dependence (Petersen, 2009). This approach is in line with the method of Bao and Edmans (2011). However, they cluster at bank-level, since this is their unit of analysis, this research will cluster at firm-level.

To test the first hypothesis, an OLS-regression with clustered robust standard errors will be performed for the full and different subsamples. The basic regression specification is formulated as follows:

$$CAR_{t-1,t+1}^{i} = \beta_0 + \beta_1 D_i^q + \beta_2 \text{REP\_AV}_i + \beta_3 \text{EXP\_AV} + \beta_4 \text{MASH\_AV}_i + \beta_5 \text{log\_SIZE\_AQ}_i + \beta_6 \text{log\_FEES\_AV} + \beta_7 \text{ log\_DEALV}_i + \beta_8 \text{EXP\_AQ}_i + \beta_9 \text{EXP\_TG}_i + \beta_{10} \text{PERC}_i + \beta_{11} \text{CRB}_i + \beta_{12} \text{SICSAME}_i + \beta_{13} \text{ATT}_i + \beta_{14} \text{NUMB}_i + \beta_{15} \text{NUM\_AQAV}_i + \sum \beta_{16} \text{Fixed year effects } + \sum \beta_{17} \text{Fixed country effects} + \varepsilon_{it} \tag{5}$$

Where $CAR^{i}_{t-1,t+1}$ represents the cumulative abnormal return of the firm with an event period of 3 trading days. β_0 represents the constant of the regression equation. β_1 - β_{17} are the main independent variables and the control variables. The definition and measurement of each variable are outlined in table 3 in Appendix A. ε_{it} represents the error term of the regression equation. This regression equation is in line with previous literature except for the variable *NUM_AQAV* (Allen, 1984; Forte et al., 2010; Francis et al., 2014; Loyeung, 2018).

Model 2: acquirer switching behavior

To evaluate the effect of a previous relationship with the acquirers' advisor on choosing that particular M&A advisor, the dependent variable whether the acquirer switches from its main advisor to another advisor is constructed (Chang et al., 2016; Francis et al., 2014). This variable is a dummy variable which takes the value of 1 when the acquirer switches from their main M&A advisor to another advisor in the current M&A deal. The dummy variable is equal to 0 when the acquirer retains their main M&A advisor in the current M&A transaction. Hence, this is a dichotomous variable which demands a logistic regression in order to be able to assess the effect of a lock-in on choosing a particular M&A advisor. The use of an OLS regression would be inappropriate, since the dependent variable has only two values and the assumptions of a linear regression are violated when the dependent variable is of binary nature[12] (Long & Freese, 2006). Therefore, the use of a logistic regression is favored. However, it requires some expertise to interpret the coefficients generated by the logistic regression. A logistic regression model provides coefficients which indicate how the logarithm of the odds ratio changes when the explanatory variable changes with one unit (Peng, So, Stage, & John, 2002). The coefficients predict the 'logit transformation' of change. Giving an example, when the odds ratio estimate is equal to 1 for a cross-border acquisition (*CRB*) it would indicate that the odds are the same for switching regardless whether it is a cross-border acquisition or not. An odds ratio estimate greater than one would increase the odds in switching when the acquisition is characterized as a cross-border deal. An odds ratio estimate less than one would decrease the likelihood of switching (Peng et al., 2002). The logistic regression model specification is formulated as follows, in order to test the acquirer's choice to switch to a particular M&A advisor:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 D_i^q + \beta_2 \text{REP\_MAV}_i + \beta_3 \text{EXP\_MAV} + \beta_4 \text{MASH\_MAV}_i + \quad (6)$$

$$\beta_5 \text{log\_SIZE\_AQ}_i + \beta_6 \text{log\_FEES\_AV} + \beta_7 \text{ log\_DEALV}_i + \beta_8 \text{EXP\_AQ}_i + \beta_9 \text{EXP\_TG}_i +$$

[12] Linear regression rest on the assumption of homoscedasticity, this is however violated since the variance in the error terms differs for each value (Long & Freese, 2006).

$\beta_{10}\text{PERC}_i + \beta_{11}\text{CRB}_i + \beta_{12}\text{SICSAME}_i + \beta_{13}\text{ATT}_i + \beta_{14}\text{NUMB}_i +$
$\beta_{15}\text{NUM\_AQAV}_i + \sum\beta_{16}\text{Fixed year effects} + \sum\beta_{17}\text{Fixed country effects} + \varepsilon_{it}$

Where p_i is the probability of switching to an advisor than its main M&A advisor for acquisition i. β_0 represents the constant of the regression equation. β_1 - β_{17} are the main independent variables and the control variables. Please note that REP_MAV, EXP_MAV and MASH_MAV are now related to the main advisor instead of the advisor in the current transaction. In this way, motivations why an acquirer switches from its main advisor to another can be investigated. The definition and measurement of each variable are outlined in table 3 in Appendix A. ε_{it} represents the error term of the regression equation.

4. Results

This section contains the results of both regression models. Section 4.1 presents the descriptive statistics of all variables. Section 4.2 will provide the correlation matrix between the variables. Section 4.3 will specify the results of both analyses and test the hypotheses. Lastly, additional robustness tests are executed to test whether the results are robust to changes, these findings are specified in section 4.3.2 and 4.3.4 for both analyses.

4.1. Descriptive statistics

Table 5 in Appendix C represents the descriptive statistics of the dependent variables, the independent variables and control variables for the full sample for the observation period of 2009 - 2018. The average cumulative abnormal return (*CAR1*) is positive, which reveals that the observed transactions have a positive impact on the short-term shareholder returns, on average. A company has on average a lock-in score (*D*) to its M&A advisor of 19%. This indicates that from all loan-, equity-, and bond agreements of an acquirer, on average 19% is with its M&A advisor. Approximately 30% of the whole sample switches from its main M&A advisor to another advisor (*SWITCH*). The reputation/ranking (*REP_AV*) of an advisor varies from 0 to 500 and is on average approximately 90,6. The number of deals (*EXP_AV*) an advisor executes annually is on average 49. The market share of an advisor (*MASH_AV*) varies from 0 till 45.2% and is on average 8.95%, measured annually. To get a sense which advisors are included in the sample, a summary statistic per advisor is included in table 6 in Appendix D. The large market share of 45.2% of Goldman & Sachs indicates that this advisor had a very dominant role in advising European acquirers, in a particular year. This could have some implications for the results, but there will be elaborated further on this in the conclusion. The experience of an acquirer during the observation period (*EXP_AQ*) varies from 0 till 19 and is on average 1.02. An acquirer gets a value of 0 on this variable when it has not engaged in an acquisition before the current transaction. This variable has a value of 1 when the acquirer was involved in 1 M&A deal before the current transaction. For target firms (*EXP_TG*), the average experience is much lower, resulting in an average of 0.04 deals executed by target firms. The percentage of shares owned after the transaction (*PERC*) is on average 95.86%. From all M&A transactions in the sample, 55% is characterized in a cross-border transaction (*CRB)*, which is a measure of information asymmetry. Approximately 39% of all transactions are executed in related industries (*SICSAME*). Almost all transactions were characterized as friendly takeovers, only 2% were characterized as hostile or neutral (*ATT*). The number of bidders varies from 1 to 3, which is a measure of deal complexity. The mean of this variable indicates that the majority of the transactions only had 1 bidder (*NUMB*). Lastly, the number of acquirer advisors varied from 1 to 7, which is also a measure for deal complexity (*NUM_AQAV*).

The number of deals sorted by the acquirers' nation can be found in table 7 in Appendix E. Since acquirers located in the nations the United Kingdom and France are overrepresented and the fact that the dataset is characterized as unbalanced, country fixed effects are controlled for.

Furthermore, it is worth mentioning that higher ranked M&A advisors have on average less lock-in to an acquirer than a lower ranked M&A advisor. This can be seen in table 8 in Appendix F. The top 25% M&A advisors have less lock-in with an acquirer than the bottom 25% M&A advisors. Also, looking at table 9 in Appendix F it becomes clear that the standard deviation within the 25% top M&A advisors is much less than the standard deviation in the 25% bottom M&A advisors.

4.2. Correlation matrix

Table 10 in Appendix G reports the Pearson's correlation matrix for all variables in the different regression analyses for the whole sample. Most correlation coefficients are between a range from -0.5 to 0.5. This indicates that there is little or no correlation between the independent variables in the dataset. Variables which have a correlation value exceeding the range of -0.5 and 0.5 could experience moderate multicollinearity. However, some variables do report high correlation coefficients, which could indicate multicollinearity if the values exceed the range of -0.7 and 0.7 (George & Mallery, 1999). The variable *EXP_AV* is highly correlated with *REP_AV* (r = -0.628*) and *MASH_AV* (r = 0.810*). Nevertheless, these high correlations can be justified, since the number of deals an advisor executes on an annual basis (*EXP_AV*), determines its market share. Furthermore, the relatively high negative correlation with the ranking of an advisor can be explained by the fact that the higher the advisor scores on the league table ranking (*REP_AV*), the more mandates it will probably obtain (*EXP_AV*). Likewise, the variable *log_SIZE_AQ* has a positive correlation coefficient with *log_DEALV* (r = 0.711*) and *log_FEES_AV* (r = 0.677*). This can also be justified, because a large acquirer (*log_SIZE_AQ*), would probably engage in M&A transactions with a great deal value (*log_DEALV*) and probably pay higher fees to its financial advisor (*log_FEES_AV*). Another strikingly high correlation is reported between *log_DEALV* and *log_FEES_AV* (r = 0.998*). This indicates that the two independent variables are almost identical or move the same. This extremely high correlation can be explained by the fact that advisory fees exist of a sufficiently large part out of success fees. These success fees are commonly calculated over the transaction enterprise value, which explains the magnitude of the correlation (Walter, Yawson, & Yeung, 2008).

The several high correlations between the explanatory variables could be an indication for multicollinearity. This phenomenon occurs when two or more independent variables are strongly correlated. This implies that at least one of the independent variables can be predicted by the model itself. Multicollinearity has an impact on the coefficients estimated, due to the linear predictability of the variables (O'brien, 2007). The variance inflation factors (VIF) of the explanatory variables is calculated to determine whether multicollinearity is a problem in the research. The results are represented in Appendix H table 11. As expected, the VIF values for *log_DEALV* and *log_FEES_AV* are extremely high, which indicates that these variables suffer from multicollinearity. When *log_FEES_AV* is left out, the variables are within the critical value range of 10, see table 12 in Appendix H. Therefore, these variables will not be used in the same regression model, which should cause multicollinearity not to be an issue in this research (O'brien, 2007).

4.3. Regression results

4.3.1. Analysis 1: acquirer cumulative abnormal returns

In this paragraph, the main results with regards to the first two hypotheses are outlined. These first two hypotheses state that there is no association between the reputation of an acquirer advisor and a negative association of a previous relationship with the advisor on the deal performance. Table 1 represents the results of the different OLS-regressions on the performance of the acquiring firm, measured in CARs with an event window of -1, +1 trading days. Model 1 incorporates only the control variables on the full sample. Model 2 includes the first independent variable (*D)*. Model 3 also incorporates the second dependent variable (*REP_AV*). Two separate models are executed to assess the distinct effect of both variables on the acquirer's performance. In addition, to test whether the results differ for top-tier and non-top-tier advisors, additional regressions are executed for two subsamples with the top 25% advisors and the bottom 25% advisors.[13]

The first hypothesis predicts that there is no association between the use of a top-tier M&A advisor and the acquirer announcement returns. Since the reputation of an advisor is measured on a scale from 1 to 500 (1 for the best financial advisor) a positive relationship between *REP_AV* and post-acquisition performance indicates that a lower ranked advisor (e.g. advisor which is ranked 500) leads to higher deal performance. Model 2 reports a small negative and insignificant coefficient for *REP_AV* ($\beta = -0.00167$). This implies that better-ranked advisors yield slightly better deal performance, this effect is however not significant. The effect is more negative in the subsample where only the 25% top-tier advisors are included, model 4. However, the effect is still rather small and not significant ($\beta = -0.0103$). Model 5 only includes the lowest 25% ranked advisors and reports a positive and significant effect of *REP_AV* on the cumulative abnormal return of the acquirers ($\beta = 0.00917$, $p < 0.05$). This implies that within the lowest quartile of M&A advisors, higher ranked advisors yield slightly lower deal performance. In comparison with earlier research, the same inconclusive results are reported. Therefore, the first hypothesis can be accepted, indicating that there is no association between the use of a higher ranked M&A advisor and takeover acquirer announcement returns.

[13] These subsamples are eventually chosen, since the model is still a good fit for these subsamples. Other subsamples are tested (upper and lower 10% of acquirers'advisors), but lead to too many omitted variables due to less variation within the subsamples.

TABLE 1: OLS REGRESSION RESULTS ON CUMULATIVE ABNORMAL RETURNS (-1, +1)

VARIABLES	Expected relationship	(1) Controls only	(2) Reputation	(3) Lock-in & reputation	(4) Top-Tier	(5) Low-Tier
D	-			-0.239	-2.473	0.831
				(0.643)	(2.645)	(1.329)
REP_AV	-/+		-0.00167	-0.00167	-0.0103	0.00917*
			(0.00208)	(0.00208)	(0.353)	(0.00431)
EXP_AV	-	-0.000152	-0.00300	-0.00326	-0.0196	0.0922*
		(0.00825)	(0.00891)	(0.00895)	(0.0189)	(0.0459)
MASH_AV	-	0.0204	0.0234	0.0239	0.129	12.16
		(0.0319)	(0.0320)	(0.0321)	(0.154)	(18.14)
log_SIZE_AQ	-	-0.688***	-0.698***	-0.701***	-1.030***	-0.497+
		(0.118)	(0.119)	(0.120)	(0.292)	(0.261)
log_DEALV	-	0.468***	0.446***	0.441***	0.751*	0.342
		(0.122)	(0.122)	(0.124)	(0.362)	(0.376)
EXP_AQ	+	-0.0124	-0.0177	-0.00981	0.104	0.153
		(0.0629)	(0.0632)	(0.0671)	(0.248)	(0.265)
EXP_TG	+	0.107	0.110	0.0964	-0.0404	-3.510*
		(0.468)	(0.469)	(0.471)	(0.881)	(1.373)
PERC	-	-0.0221*	-0.0222*	-0.0219*	-0.0310	-0.0643
		(0.0109)	(0.0109)	(0.0109)	(0.0259)	(0.0498)
CRB	-	-0.270	-0.274	-0.293	-0.0955	-0.169
		(0.429)	(0.429)	(0.430)	(0.844)	(1.684)
SICSAME	+	0.0520	0.0427	0.0452	-0.624	0.104
		(0.387)	(0.387)	(0.387)	(0.776)	(1.015)
CASH	+	0.000760	0.000613	0.000640	-0.00513	0.00591
		(0.00410)	(0.00410)	(0.00411)	(0.00710)	(0.0126)
ATT	+	1.088	1.089	1.092	-0.0638	2.725
		(0.757)	(0.758)	(0.765)	(1.933)	(2.800)
NUMB	-	-1.886***	-1.918***	-1.898***	-1.722	
		(0.479)	(0.486)	(0.488)	(1.095)	
NUM_AQAV	-	-0.312	-0.299	-0.299	-0.184	-0.241
		(0.242)	(0.242)	(0.242)	(0.426)	(1.405)
Constant		4.644*	5.052**	5.115**	10.80	-0.671
		(1.844)	(1.910)	(1.922)	(6.739)	(6.115)
Observations		1,127	1,127	1,127	314	246
R-squared		0.069	0.070	0.070	0.188	0.110
Country FE		Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes

Table 1 presents the OLS regressions on *CAR (-1, +1)*. Model 1 only incorporates control variables. Model 2 only incorporates *REP_AV* as main independent variable. Model 3 incorporates both *REP_AV* and *D* as main independent variables. Model 4 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 5 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

The second hypothesis predicts that there is a negative association between a previous relationship with a M&A advisor and the takeover acquirer announcement returns. Model 3 reports a negative and insignificant effect between relationship intensity with a M&A advisor (*D*) and the acquirers' abnormal return ($\beta = -0.239$). The effect is even more negative ($\beta = -2.473$) when looking at the subsample of model 4, which only incorporates the 25% top-tier advisors. An opposite effect is reported ($\beta = 0.831$) when looking at the subsample of model 5, which only incorporates the 25% lowest-ranked advisors. The overall effect is negative, indicating that the larger the previous relationship with an advisor, the lower the deal performance. This effect is even more pronounced when only incorporating top-tier advisors. For the lowest-ranked advisors, the opposite is true, the more intense the previous relationship with a low-ranked advisor, the higher the abnormal return. However, all coefficients regarding the previous relationship with an advisor are not significant. Therefore, the second hypothesis cannot be accepted.

Regarding the control variables, the model shows the expected signs except for *MASH_AV*, *log_DEALV* and *EXP_AQ*. Strikingly, *log_DEALV* shows a strong significant and positive relationship with the acquirer abnormal returns ($\beta = 0.441$, $p < 0.001$). This implies that a higher transaction value yields higher acquirer abnormal returns, this is in accordance with previous research (Loyeung, 2018). Also, the variable *EXP_TG* shows an opposite relationship as expected in model 4 and 5 and is significant in model 5 ($\beta = -3.510$, $p < 0.05$). This implies that when a target is more experienced in M&A transactions, the cumulative abnormal returns of the acquirer tend to get lower when the advisor of the acquirer is amongst the lowest ranked advisors. One potential reason could be that these lowest-ranked advisors are not able to positively bargain with experienced targets, resulting in a less favorable deal for the acquirer. Moreover, *EXP_AV* shows an opposite and significant relationship in model 5 ($\beta = 0.0922$, $p < 0.05$). Indicating that within the lowest-ranked advisors, a more experienced M&A advisor does create value for the acquiring firm. Lastly, the control variables *SICSAME*, *CASH* and *ATT* do not show their expected signs when looking at model 4. However, none of these variables are significant.

The explanatory power of the models is relatively low. However, this is in line with previous research (L. Allen et al., 2004; Bao & Edmans, 2011; Loyeung, 2018).

4.3.2. Analysis 1: robustness checks

Additional tests are executed to assure the reliability of the test results. First of all, the main analysis is also executed without country and year fixed effects to test the statistical validity of the models. As can be seen in table 13 of Appendix I, the coefficients are approximately the same and report the same direction as the main analysis. Since the explanatory power (R^2) of the models which include time and country fixed effects nearly doubled, incorporating time and country fixed effects is preferred.

Furthermore, a robustness test on a wider event window (-5, +5) is included to check if the observed results are no consequence of the selected event period. Table 14 in Appendix I reports these findings. When choosing this event window, a negative and insignificant coefficient for *REP_AV* (β = -0.00320) is reported for the full sample. The coefficient for the low-tier subsample shows the same sign but is no longer significant (β = 0.00980). The coefficient for the top-tier subsample is still insignificant, but reports an opposite relationship in comparison with the main analysis (β = 0.618). The implication is that within the top-ranked advisors, higher ranked advisors yield lower acquirer abnormal returns when considering a longer event window. All coefficients regarding the reputation of the M&A advisor are still not significant, so the first hypothesis remains accepted, no association can be made between the use of a higher ranked M&A advisor and takeover acquirer announcement returns.

Considering the second hypothesis, the same sign shift occurred. Still, a negative and insignificant coefficient for *D* is reported for the full sample (β = -0.370). The low-tier subsample still shows a positive insignificant coefficient (β = 0.572). And again, the coefficient for the top-tier subsample is still insignificant, but reports an opposite relationship in comparison with the main analysis (β = 0.734). Thus, for both variables the top-tier subsample reports opposite insignificant relationships in comparison with the main analysis. Still, since no result is significant, the acceptance or rejection of the first two hypotheses remain unchanged. Also, due to the lower explanatory power of the model and the fact that some control variables now show an opposite sign as expected, the event window of 3 trading days is preferred.

Moreover, a robustness test is performed where *log_FEES_AV* is incorporated and *log_DEALV* is left out. Table 15 in Appendix I reports these findings. The explanatory power of the model is lower. Therefore, the model with *log_DEALV* is preferred. Two changes took place which are worth mentioning. First of all, in the top-tier sample, an opposite but still insignificant coefficient is reported for *REP_AV* (β = 0.0973). Second, *ATT* shows a significant and negative relationship with *CAR*, indicating that within the top-tier sample, a friendly takeover leads to less takeover announcement returns for the acquirer (β = -2,666; $p < 0.05$).

Another robustness check is executed by altering the measurement of a potential lock-in to a M&A advisor. Whereas in the previous analyses a potential lock-in was measured by a ratio variable which measured the intensity of the relationship with the advisor, table 16 in Appendix I reports the results when a lock-in is measured using a dummy variable. In model 1, 3 and 5 the dummy variable *D_5* takes a value of 1 when the acquirer has had any relationship with its M&A advisor in the preceding 5 years. In model 2, 4 and 6 the dummy variable *D_2000* has a value of 1 when the acquirer has had any relationship with its M&A advisor from the year 2000 onwards.[14] The aim of this robustness test is to check whether the results are the same when incorporating a broader measure for a lock-in. Instead of measuring a previous relationship with a dollar-weighted ratio, the variable is measured whether there was a relationship with the advisor at all. The findings show the same results. Only the coefficients for *D_5* and *D_2000* in the top-tier subsample show less negative coefficients ($\beta = -0.222$; $\beta = -0.209$) in comparison with the main analysis.

One last robustness check is performed to check whether the results change when the 57 observations, which were not present in the top 500 league tables, are left out. These observations received a value of 0 for advisor experience and market share (*EXP_AV; MASH_AV*) and a ranking of 500 for advisor reputation (*REP_AV*). The results are outlined in table 17 in Appendix I. What immediately stands out is that *REP_AV* has the same sign, but is now significant ($\beta = -0.00815$, $p < 0.05$) in model 3. Thus, when leaving out the transactions advised by the lowest-ranked advisors, a better-ranked advisor leads to improvement of deal performance. However, this effect is very small. Furthermore, the coefficient for *REP_AV* in model 5 is not significant anymore ($\beta = 0.0139$), whereas it was significant in the main analysis. So, when leaving out the lowest ranked M&A advisor in the low-tier subsample, the analysis has not enough power to conclude that better ranked low-tier advisors lead to lower deal performance. The fact that the coefficient *REP_AV* in model 3 is rather small and the coefficient in model 5 is not significant anymore does not change the acceptance or rejection of the first hypothesis. With regards to the second hypothesis, only the coefficient for *D* in model 5 has become more positive ($\beta = 1.377$), the rest is approximately the same. Nonetheless, none of the coefficients is significant, so the second hypothesis can still not be accepted.

Overall, the robustness tests show that the results are robust to changes and that the first hypothesis can be accepted and the second hypothesis cannot be accepted.

[14] This specific year is chosen due to data availability.

4.3.3. Analysis 2: acquirer switching behavior

In this paragraph, the main results with regards to the third and fourth hypotheses are outlined. The third hypothesis states that there is a positive association between the ranking of a M&A advisor and hiring the advisor for the M&A transition. The fourth hypothesis states that there is a positive association between a previous relationship with an advisor and hiring the advisor for a M&A transaction.

Table 2 represents the results of the different logistic-regressions on whether an acquirer switches to another M&A advisor. Model 1 only incorporates the control variables on the full sample. Model 2 includes the first independent variable (*REP_MAV)*. Model 3 also incorporates the second dependent variable (*D_MAV*). Two separate models are executed to assess the distinct effect of both variables on the acquirer's performance. In addition, to test whether the results differ for top-tier and non-top-tier advisors, additional regressions are executed for two subsamples with the top 25% advisors and the bottom 25% advisors.

Each model reports estimates for the change in the odds ratio, the standard errors, the pseudo R^2, the Wald Chi-square and the log-likelihood. The pseudo R^2 of a logistic model is similar to the R^2 in an OLS-regression, in the sense that it explains the overall fit of the model. However, one must be careful with extrapolating the definition of the OLS R^2 to a logistic regression. What certainly applies is that higher values of pseudo R^2 indicate a better explanatory power of the model (Fox, 1997). The pseudo R^2 in the models below are moderate, this is in accordance with previous literature (Forte et al., 2010). The significant Wald Chi-square test results indicate that including the predictors into the model leads to a statistically significant improvement in the model fit in comparison with the situation where the model has only a constant (Johnston & DiNardo, 2000).

One important aspect to take into account is that the dependent variable is operationalized as whether the acquirer has switched from its main advisor to another advisor in the current transaction. It gets a value of 1 when it has switched to another advisor.[15] Another important aspect to consider is that the variables which measure characteristics of advisors are related to the main advisors and not the current advisor in the transaction.[16] In this way, it is possible to track down the motivations for switching from the main advisor to another advisor. The results of this regression are reported in table 2.[17]

Model 2 predicts a significant odds ratio estimate between *REP_MAV* and switching ($\beta = 1.002$, $p < 0.05$). This value is very close to 1, implying that the ranking of a financial advisor has little effect on the likelihood of switching from the main M&A advisor to another advisor. This estimate is stable in model 3 and 5, but changes in model 4, which only represents the top-tier M&A advisors. This estimate is greater than 1 ($\beta =$

[15] The number of observations in this analysis has reduced due to incorporating year and country fixed effects in comparison with the previous analysis. An additional robustness check is also executed for this analysis to assure reliability of incorporating year and country fixed effects.

[16] A robustness check is incorporated where advisor characteristics are not related to the main advisor, but to the advisor in the current deal.

[17] The number of variables in the low-tier subsample decreased due to the reduction in observations. Incorporating these variables would lead to multicolliniearity and biased results, due to less variation in this subsample.

1.178), indicating that a higher ranking of the main top-tier M&A advisor decreases the likelihood of switching to another advisor.[18] However, this effect is not significant. The coefficients in model 2, 3 and 5 are very close to one and significant, which implies that in general the reputation of the main advisor does not increase the probability to switch to another advisor. Therefore, the third hypothesis cannot be accepted.

With regard to the last hypothesis, model 3 predicts a significant odds ratio estimate, which is less than 1 for the lock-in variable *D_MAV* ($\beta = 0.508$, $p < 0.05$). So, the likelihood of switching to another M&A advisor decreases when the acquirer relationship with the main advisor is more intense. This result does not hold for top-tier M&A advisors. This estimate indicates that a previous relationship with the main M&A advisor increases the likelihood of switching to another advisor ($\beta = 1.367$). However, this result is not significant. Lastly, the same relationship between a lock-in and switching behavior within the low-tier subsample is found, only less significant ($\beta = 0.309$, $p < 0.1$). The overall effect is significant and in accordance with the last hypothesis. Therefore, the fourth hypothesis can be accepted.

Regarding the control variables, the model shows the expected signs, except for *MASH_MAV*, *PERC*, *SICSAME*, *ATT*, *NUMB*. For the variables *MASH_MAV*, *PERC* and *SICSAME* the change in odds ratio lie very close to 1, indicating that there is no or a negligible effect of these variables on the probability of switching to another advisor. The variables *ATT* and *NUMB* show an opposite effect on switching to another advisor, but these variables are not significant. The explanatory power (measured in Pseudo R^2) is in accordance with previous literature (Forte et al., 2010).

[18] The variable *REP_AV* is measured on a scale from 1 to 500, where the highest ranked advisors have the lowest ranking/value on this variable. Since the odds ratio variable in model 4 is higher than 1, this indicates that a lower advisor ranking (higher value for this variable) increases the likelihood of switching to another advisor and vice versa.

TABLE 2: LOGISTIC REGRESSION RESULTS ON SWITCHING BEHAVIOR

VARIABLES	Expected relationship	(1) Controls only	(2) Reputation	(3) Lock-in & reputation	(4) Top-Tier	(5) Low-Tier
D_MAV	-			0.508*	1.367	0.309+
				(0.147)	(1.055)	(0.186)
REP_MAV	+		1.002*	1.002*	1.178	1.004*
			(0.000813)	(0.000810)	(0.128)	(0.00180)
MASH_MAV	-	0.999	0.997	0.998	1.038	
		(0.0128)	(0.0130)	(0.0129)	(0.0669)	
EXP_MAV	-	1.000	1.003	1.002	1.004	1.044**
		(0.00350)	(0.00374)	(0.00371)	(0.00715)	(0.0137)
log_SIZE_AQ	+	1.328***	1.349***	1.336***	1.313*	
		(0.0705)	(0.0728)	(0.0727)	(0.146)	
log_DEALV	+	1.009	1.028	1.014	1.127	1.111
		(0.0552)	(0.0575)	(0.0576)	(0.159)	(0.135)
EXP_AQ	+	1.123+	1.129+	1.159*	1.601***	1.155
		(0.0766)	(0.0755)	(0.0783)	(0.225)	(0.170)
EXP_TG	0	0.820	0.813	0.786	0.503	4.434
		(0.266)	(0.262)	(0.249)	(0.301)	(5.856)
PERC	+	0.995	0.995	0.996	0.998	0.983
		(0.00672)	(0.00672)	(0.00670)	(0.0144)	(0.0174)
CRB	+	1.440+	1.447+	1.366	0.942	0.912
		(0.281)	(0.282)	(0.268)	(0.323)	(0.491)
SICSAME	-	1.089	1.104	1.120	1.040	1.859
		(0.181)	(0.184)	(0.188)	(0.323)	(0.776)
CASH	0	0.999	1.000	1.000	0.999	1.006
		(0.00166)	(0.00167)	(0.00168)	(0.00322)	(0.00424)
ATT	-	1.619	1.584	1.588	1.901	
		(0.711)	(0.695)	(0.701)	(1.760)	
NUMB	+	0.626	0.646	0.672	0.163	
		(0.390)	(0.408)	(0.435)	(0.315)	
NUM_AQAV	+	1.196+	1.187+	1.186+	1.420*	0.808
		(0.121)	(0.121)	(0.121)	(0.234)	(0.326)
Constant		0.0425*	0.0265**	0.0328**	0.00744	0.340
		(0.0546)	(0.0347)	(0.0430)	(0.0229)	(0.746)
Observations		1,097	1,097	1,097	302	248
Country FE		Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes
Pseudo R		0.152	0.156	0.160	0.247	0.161
Wild Chi-square		136.1***	141***	159***	148.4***	44.27*
Log-likelihood		-570	-567.9	-564.9	-154.9	-96.01

Table 2 presents the logistic regressions on switching behavior, where the advisor characteristics are related to the main advisor. Model 1 only incorporates control variables. Model 2 only incorporates *REP_MAV* as main independent variable. Model 3 incorporates both *REP_MAV* and *D_MAV* as main independent variables. Model 4 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 5 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

4.3.4. *Analysis 2: robustness checks*

Additional tests are executed to assure the reliability of the logistic test results. The first four robustness checks are executed in accordance with section 4.3.2 and the remaining robustness checks are executed which specifically test the measurement of switching behavior.

First of all, the main analysis is also executed without country and year fixed effects to test the statistical validity of the models. As can be seen in table 18 in Appendix J, the coefficients are approximately the same and report the same direction as the main analysis. However, the models regarding the top-tier subsamples do report two changes which are worth mentioning. The coefficient for *D_MAV* shows an opposite relationship, but is still not significant ($\beta = 0.790$). The coefficient for *REP_MAV* is now smaller and significant ($\beta = 1.064$, $p < 0.1$). Since the coefficient is very close to 1, this implies that also for the top-tier subsample reputation of the main advisor has little effect on the switching behavior of acquirer firms. Since the explanatory power (Pseudo R) of the models which include time and country fixed effects is higher, incorporating time and country fixed effects is preferred.

Moreover, a robustness test is performed where *log_FEES_AV* is incorporated and *log_DEALV* is left out. Table 19 in Appendix J reports these findings. Overall, the number of observations decreased and the explanatory power (Pseudo R) is higher in the main analysis. When incorporating *log_FEES_AV*, this variable is only significant in model 2 ($\beta = 1.326$, $p < 0.1$). This implies that higher fees encourage switching from the main advisor to another advisor. However, given the fact that the significance of the other variables in model 2 decreased and the model only slightly improved (in terms of Pseudo R), the models which incorporate *log_DEALV* are preferred.

In accordance with the first analysis, a robustness check is executed by altering the measurement of a potential lock-in to a M&A advisor. Table 20 in Appendix J reports these findings when incorporating the two dummy variables. The results show approximately the same odds ratio coefficients. However, the variables which measure the lock-in are only significant in the models which include the low-tier subsamples ($\beta_{D\_5MAV} = 0.320$, $p < 0.1$; $\beta_{D\_2000MAV} = 0.269$, $p < 0.05$). But still, the results indicate that a previous relationship with the main advisor decreases the chance to switch to another advisor. When looking at model 3 and 4, the changes in odds ratios are approximately the same as in the main analysis ($\beta_{D\_5MAV} = 1.179$, $\beta_{D\_2000} = 1.371$). However, the estimates are still not significant. With regards to the other explanatory variable, significant coefficients are reported for all models. Even for the top-tier subsamples in model 3 ($\beta = 1.103$, $p < 0.01$) and model 4 ($\beta = 1.107$, $p < 0.01$). These results show that within the top-tier subsample, an advisor with a lower ranking increases the probability to switch from the main advisor to another. Or to put it differently, an advisor with a higher ranking decreases the probability to switch to another advisor. Thus in the top-tier subsample, a higher ranked advisor decreases the likelihood that the acquirer switches from its main advisor to another advisor, while in the full sample no association between the ranking of an advisor and acquirers' switching behavior can be made.

Furthermore, a robustness check is executed to check whether the logistic regression results change when the 57 observations, which were not present in the top 500 league tables, are left out. The results are reported in table 21 in Appendix J. Overall, the results are approximately the same, with the most important changes in model 3. First of all, the lock-in variable *D_MAV* is not significant anymore. Secondly, *REP_MAV* (β = 1.014, $p < 0.05$) is slightly higher. Thus, when leaving out the lowest ranked advisors, the change in odds ratio estimates slightly increased, implying that a higher reputation of the main advisor decreases the chance to switch to another advisor.

Additionally, four robustness checks are performed which specifically apply to the second analysis. As mentioned in section 3.2, the measurement of the dependent variable, whether an acquirer switches from a M&A advisor has important implications. Therefore, a robustness check is executed in which observations where the acquirer switches from M&A advisor every time and when an acquirer only executed one deal, are left out. The results of the robustness checks are outlined in table 22 in Appendix J. What immediately stands out is the large and significant odds ratio coefficient for *D_MAV (*β = 37.81, $p < 0.05$) and an inflated standard error in model 2. This makes the found relationship between a lock-in to an advisor in the top-tier subsample and acquirers' switching behavior questionable. This finding is due to a reduction in observations and the fact that this model is controlled for country fixed effects.[19] Model 3 reports the same analysis but does not control for country fixed effects. Since the standard error still shows no representative value, there cannot be made a meaningful association between a lock-in and acquirers' switching behavior within the top-tier subsample. With regards to *REP_MAV*, the coefficients for the full and low-tier subsample are approximately the same. And again, the top-tier subsample reports an even more significant coefficient (β = 1.390, $p < 0.01$). Implying that a higher ranked advisor within this subsample decreases the probability to switch to another advisor.

Furthermore, two robustness checks are incorporated where advisor characteristics are not related to the main advisor, but to the advisor in the current deal. These robustness checks are executed to be able to track down the motivations for switching to the current advisor. The results of the first regression where the dependent variable is switching behavior, are outlined in table 23 in appendix J. Model 2 predicts a significant odds ratio estimate between *REP_AV* and switching (β = 1.002, $p < 0.1$). This value is very close to 1, implying that the ranking of a financial advisor has little effect on the likelihood of switching from the

[19] The subsample is double checked for multicollinearity and influential cases. It is found that by incorporating country dummy variables some variables perfectly predict the chance that an acquirer switches from its main to another advisor. To address this, a model without fixed effects is included, model 3.

main advisor to the other advisor. This estimate is stable in model 3 and 5, but changes in model 4, which only represents the top-tier M&A advisors. The estimate is significant and less than 1 ($\beta = 0.645$, $p < 0.01$), indicating that a higher ranking within the top-tier M&A advisors increases the likelihood of switching to the advisor[20]. Again, this implies that in general the reputation of an advisor does not increase the probability of switching, except for advisors which are already characterized as a top-tier advisor.

With regard to the last hypothesis, model 3 predicts a significant odds ratio estimate which is less than 1 for the lock-in variable *D* ($\beta = 0.241$, $p < 0.001$). This implies that a larger previous relationship with the current advisor decreases the likelihood of switching to this M&A advisor. This result is stable over model 4 and 5, but less or not significant anymore.

To confirm the regression results of the last robustness check, another robustness check is executed to check why acquirers would stay with their main advisor. The advisor characteristics are again related to the advisor in the current deal. However, the dependent variable now becomes whether the acquirer retains their main advisor in the current M&A transaction[21]. The results are reported in table 24 in Appendix J. Model 2 predicts a significant odds ratio estimate, which is close to 1 between *REP_AV* and retaining the current advisor ($\beta = 0.998$, $p < 0.001$). This indicates that the ranking of a financial advisor has little effect on whether an acquirer retains its main advisor. This estimate is stable in model 3 and 5, but changes in model 4. This estimate is significant and greater than 1 ($\beta = 1.551$, $p < 0.01$). This indicates that lower ranking of current advisor increases the probability that the main advisor will be retained. Furthermore, a higher previous relationship with the current advisor increases the probability that the main advisor will be retained ($\beta = 4.150$, $p < 0.001$).

Finally, to confirm the regression results of the main analysis, a last robustness check is incorporated to confirm the observed relationship when incorporating characteristics of the main advisor on the dependent variable whether an acquirer retains its main advisor. The results are outlined in table 25. These results confirm the earlier observed relationships. A larger previous relationship with the main advisor increases the probability that an acquirer stays with the advisor, indicated by the odds ratio coefficient of *D_MAV* ($\beta = 1.968$, $p < 0.05$). In addition, the coefficients for *REP_MAV* are significant and close to 1, indicating that the reputation of an advisor has little effect on whether an acquirer retains its main advisor. However, this effect is not significant for the top-tier subsample.

Overall, the robustness checks confirm the rejection of the third hypothesis and acceptance of the fourth hypothesis. However, one should note the significant odds ratio estimates for *REP_MAV* and *REP_AV* for

[20] The variable *REP_AV* is measured on a scale from 1 to 500, where the highest ranked advisors have the lowest ranking/value on this variable. Since the odds ratio variable in model 4 is lower than 1, this indicates that a lower advisor ranking (higher value for this variable) decreases the likelihood of switching to the advisor and vice versa.

[21] This variable is equal to 1 when the acquirer retains is main advisor in the current transaction and 0 otherwise.

the top-tier subsamples in the robustness checks represented in table 20, 22, 23 and 24 in Appendix J. These significant findings could have implications for the rejection of the third hypothesis for the top-tier subsample. This will be explained further in the conclusion & discussion.

5. Discussion & Conclusion

Due to the rapid economic development, the magnitude of M&A activity is increasing and so is the influence of large investment banks. A growing body of research has investigated whether these so-called high-quality advisors provide superior deal performance. Since there is no consensus if high-quality investors yield higher post-acquisition performance and why acquirers choose specific advisors, this study focuses on whether a previous relationship with a M&A advisor affects both the deal outcome and the choice to hire the M&A advisor for acquirers located in Europe. In order to provide an answer to the research question, the reputation of a M&A advisor should also be considered when assessing the effect of a lock-in on the deal outcome and the choice to hire an advisor. Therefore, four hypotheses were developed to determine the effect of advisor reputation and a lock-in on both cumulative abnormal returns and switching behavior of an acquirer. This chapter continues by discussing the findings of the previous chapter and going through the formed hypotheses. These findings will also be compared with prior research results. Hereafter it will provide a brief conclusion of the research and elaborate on its contributions, limitations and recommendations for further research.

5.1. Discussion and interpretation of the results

The results of the first analysis show that in general, the use of a higher ranked M&A advisor does not significantly increase acquirer cumulative abnormal returns. In addition, within the low-tier advisor subsample, higher ranked advisors even lead to a small and significant decrease of acquirer cumulative abnormal returns. However, the latter finding is not significant when leaving out the advisors with the lowest ranking. On the other hand, when looking at the complete sample, a higher ranking of a M&A advisor leads to a small significant improvement of deal performance when leaving out these observations. So, when reviewing the results, two significant opposite relationships regarding deal performance can be found in the full sample and in the low-tier subsample, when an advisor has a better reputation. Since the significant decrease in the low-tier subsample of the main analysis is very small and the significant increase in the full sample of the robustness check in table 17 in Appendix I is also very small, it can be concluded that a higher ranked advisor does not lead to a sufficient improvement in deal performance. Therefore, no association can be made between the ranking of a financial advisor and deal performance of acquirers located in Europe.

Another key finding in the first analysis is that a previous relationship with an advisor of a deal does not lead to a significant decrease in cumulative abnormal returns for the acquirer. This holds for the full samples and the top-tier subsamples. When looking at the low-tier subsample an insignificant positive relationship can be found. Indicating that a previous relationship with a low-tier M&A advisor improves the deal performance. These results are also reflected in each robustness check. However, none of the coefficients for a lock-in on CAR is significant. Therefore, it can be concluded that there is no association between a lock-in to a M&A advisor and its effect on deal performance.

Since no association can be made between the reputation and a lock-in on deal performance, the question rises why acquirers choose specific advisors in the first place. This question is addressed in the second analysis, where a logistic regression is performed to examine why acquirers switch from their main advisor to another advisor. In general, the reputation of an advisor does not increase the probability of switching from the main advisor to another advisor. On the contrary, a higher ranked advisor within the top-tier advisors decreases the probability to switch from the main advisor to another advisor. This finding is confirmed in table 23 in Appendix J, where the motivations to switch from the main advisor to the current advisor are examined by incorporating characteristics of the current advisor. A higher ranking by the current advisor increases the likelihood to switch to this advisor, when looking at the top-tier subsample. When considering each subsample characteristics regarding reputation in table 9 in Appendix F, it can be observed that the difference in standard deviations between subsample 1 and 4 is very large. This is also reflected in table 6 in Appendix D, where all advisors and their minimum and maximum ranking are outlined. The spread between the minimum and maximum ranking for each advisor increases when the list moves down. The small standard deviation within the top-tier subsample indicates that there are only small differences between the ranking of advisors in the top-tier sample. Maybe acquirers advised by top-tier advisors are more eager to switch based on reputation, since the reputation of top-tier advisors are very close to each other, which makes switching to another advisor more obvisous and they just choose an advisor which charges for instance the lowest advisory fees. Since the latter was significant in the robustness check in table 19 Appendix J. A reason why switching based on reputation does not occur in the full sample and low-tier sample is perhaps the fact that the market is dominated by some large investment banks, as can be seen table 6 in Appendix D and the summary statistics in table 5 in Appendix C. The European M&A market is on average almost entirely dominated by the first 12 investment banks. This might indicate that switching between lower ranked M&A advisors is discouraged because the vast market share is already taken by large investment banks.

Furthermore, the effect of a lock-in to a M&A advisor on switching behavior by the acquirer is examined. In general, a more intense previous relationship with the advisor decreases the chance that an acquirer switches from this advisor to another advisor. However, this finding does not hold for the 25% top-tier advisors, since these findings are not significant in each analysis. When performing the analysis based on current advisor characteristics, it is found that a previous relationship with this advisor increases the probability that the main advisor will be retained (table 24 in Appendix J; $\beta = 4.150$, $p < 0.001$). This means that a relationship with the current advisor is not a determinant to switch to this advisor.

5.2. Findings in comparison with prior research

Several lessons can be drawn from the results of this study. As previously stated, it can be concluded that there is no association between the reputation of a M&A advisor and deal performance. When looking at prior research the findings vary considerably. On the one hand, no higher merger outcomes are reported when using a higher ranked advisor (Chang et al., 2016; Servaes & Zenner, 1996). On the other hand, some authors do report higher cumulative abnormal returns when a top-tier financial advisor is hired (Bao & Edmans, 2011; Forte et al., 2010). The findings of this research could differ since previous research only investigates the effect of using a top-tier advisor, while this research incorporates all top 500 league table advisors to evaluate whether reputation in general affects deal outcome. Also, one should take into account that the research of Bao & Edmans (2011) is aimed at acquirers engaging in a merger between 1980 and 2007 and that the research of Forte et al. (2010) only examines European targets from 1994 till 2003. There are two potential reasons which could explain why the results regarding reputation and the effect on deal performance differ. First, both studies included a period of uncertainty (e.g. S&L crisis U.S. or the global dotcom bubble). It is expected that the certifying role of banks is larger when uncertainty is an important characteristic of the market. Since periods of uncertainty are often characterized as nontransparent periods where information asymmetry is high, more prestigious banks ought to decrease this uncertainty by their comparative information and efficiency advantage (Capizzi et al., 2017). Since the researches of Forte et al. (2010) and Bao & Edmans (2011) was executed by using transactions sample where uncertainty and irrational market behavior played an important role, banks could be better capable of certifying higher deal performance. By way of contrast, this study purposefully not included a crisis within the research. So, maybe higher ranked advisors are only able to capture higher deal performance in times of uncertainty.

Second, this research differs from the results of Bao & Edmans (2011) because they use past performance to measure the quality of an advisor, while this study uses the reputation retrieved from league tables, which are mainly based on market shares. Since both studies yield different findings, an important implication could be that the ranking in financial league tables could be misleading and acquirers should not base advisory decisions on this.

Given this implication, this research has shown that in general the reputation of a financial advisor is not a determinant to switch from M&A advisor, except for advisors which are characterized as top-tier, which is in accordance with previous research (Chang et al., 2016; Forte et al., 2010; Ismail, 2010). However, especially in the top-tier subsample no significant improvement in European acquirers' returns can be found. While reputation within this top-tier subsample is a determinant to switch from the main advisor to another.

Furthermore, this research has found that there is no association between a previous relationship with an advisor and deal performance. This is not in accordance with the results of Forte et al. (2010), which do find an increase in abnormal returns when the advisor relationship with the European target is more intense. The authors reason that these higher target abnormal returns can be attributed to the advisor due to deep knowledge about the company. One should keep in mind that investment banks are best off being at the sell side of a company, since they are certain to receive a success fee, because the target will always be sold (Forte et al., 2010). This could explain the difference in results between acquirers and target firms, because target advisors are more capable in capturing this certainty in higher deal performance.

Furthermore, the effect of a lock-in to a M&A advisor on switching behavior by the acquirer is examined. In general, a more intense previous relationship with an advisor decreases the chance that an acquirer switches from its main advisor to another advisor. The is in line with the results of Chang et al. (2016), who find that switching to another advisor is less likely when the previous relationship is stronger. In addition, the research of Francis et al. (2014) also confirms this finding, but suggests that a previous relationship has only a limited influence on switching behavior. Maybe the influence of lock-in effect in this research is higher since it focuses on acquirers located in Europe, what is usally characterized as a bank-based system where network and long-term relationships are more important (Levine, 2002). Whereas the research of Francis et al. (2014) only incorporates acquirers located in the U.S.

This research is the first study which investigates whether the characteristics of the current advisor encourage acquirers to switch from their main advisor to this advisor. It is found that a previous relationship with this advisor increases the probability that the main advisor will be retained, so a lock-in to the current advisor does not move firms to choose this advisor. Perhaps the previous loan, equity or bond transaction experience with the advisor was not satisfying, inclining acquirers not to choose the advisor. It could also be the case that acquirers are afraid of information leakage to rivals. Chang et al. (2016) conclude that acquirers switch between advisors when the advisor has some sort of relationship with the top three firms in the industry of the acquirer. This could be a reason that an acquirer does not switch to the particular advisor, when it knows that the advisor also has a relationship with an industry rival.

5.3. Conclusion, contribution, limitations & recommendations for further research

This study contributes to the existing literature by providing a better understanding of what persuades European acquirers to switch from M&A advisors and whether the characteristics of these advisors provide superior deal performance. In contrast to prior research, this study not only investigates the use of a top-tier advisor, but it takes a broader stance by evaluating whether reputation in general has an effect on both deal outcome and switching behavior. Furthermore, it examines what motivates acquirers to switch from their main advisor to another advisor, but also what characteristics of the current advisor persuades acquirers to switch to this advisor. The key findings of this study are that in general, a higher ranked advisor does not lead to higher post-acquisition performance, or that the effect is negligibly small. Especially for top-tier advisors, such a relationship is not found, while advisor ranking within this subsample is an important reason to switch from advisors. While previous studies, measuring advisor quality with past performance do report an increase in deal performance, the business implications of M&A advisors' league tables should be reconsidered. Since a higher ranking among top-tier advisor does not benefit the post-acquisition performance of European acquirers. Another key finding of this research is that a lock-in between a M&A advisor and European acquirers is an important determinant to stay with this advisor. However, a previous relationship with an advisor is not associated with higher deal performance. This indicates that long-term relationships and networks are important for advisory decisions of European acquirers. Furthermore, it is found that a previous relationship with an advisor is not a determinant to move firms to deviate from their main advisor and choose this specific advisor for their M&A advice.

Some limitations are involved when reviewing this research, these can provide a foundation for further research. First, two potential limitations can be attributed to the measurement of the explanatory variable lock-in to a M&A advisor (*D)*. This study only incorporates the lead book runner of a loan, equity or bond transaction to determine the previous relationship between the acquirer and the advisor. On the one hand, a lock-in could be too easily found when all book runners of the transaction are incorporated. On the other hand, when taking into account all these book runners maybe the greatest lock-in to a particular advisor can be determined and subsequently deviations from this advisor can be assessed. Further research could investigate whether the results change when a more comprehensive measurement of a lock-in is used.

Another potential limitation regarding the lock-in variable is that a previous relationship with an advisor might also be unobservable meaning that a corporation has an implicit relationship with the advisor. For instance, the corporation might choose a M&A advisor because it offers favorable loan agreements in the future, which are not captured yet with the current measurement of this variable. Future research could address this by using a fixed-effects model which could account for unobservable advisor characteristics.

Second, due to the lack of data availability, only European listed acquirers are included in this research. These firms are of a considerably large size, which could jeopardize the generalizability of the research results. As can be seen in the first main analysis, deals advised by smaller advisors yield different results than the full sample. It is seen that within the lowest quartile of M&A advisors, higher ranked advisors yield slightly lower deal performance. Thus, the ranking of a financial advisor among smaller deals might have different implications for deal performance than listed deals. This phenomenon could be a suggestion for future research. Another suggestion for further research is to also consider other measurements for advisor quality of European acquiring firms. In this research, advisor quality was measured by using financial league tables which are basically rested on market share. When incorporating other measurements for advisor quality such as previous announcement returns or analyst recommendations the results could have differed. Nevertheless, by using financial league tables as measurement for advisor quality, important insights regarding the usefulness of those league tables are uncovered.

6. References

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7. Appendices

Appendix A

TABLE 3: DESCRIPTION OF VARIABLES

Variable Name	Measurement	Source
	Dependent Variables	
CAR_{i,t_1,t_2}	The average (standardized) cumulative abnormal returns for the acquiring firm from day t – 1 until day t + 1, where t is the day that the deal is announced.	**Eikon**
SWITCH	Dummy variable which is equal to 1 when the acquirer switches from its main M&A advisor to another.	**Thomson**
RETAIN	Dummy variable which is equal to 1 when the acquirer retains its main M&A advisor in the current transaction.	**Thomson**
	Independent Variables	
D_i^q	Intensity of the previous relationship between the acquirer i and advisor q at the time of the deal. The intensity is dollar value of all transactions where the given M&A advisor was the lead book runner divided by the total dollar value of loan, bond and equity transactions completed by the acquirer over the last 5 year.	**Thomson**
REP_AV	Reputation of the acquirers' advisor measured as the rank position within the annual retrieved the M&A league table.	**Eikon**
	Control Variables	
Advisor controls		
EXP_AV	Number of deals executed by the acquirers' financial advisor in the particular year, retrieved annually from the M&A league table.	**Eikon**
FEES_AV	Fees charged by the financial advisor for the particular deal.	**Thomson**
MASH_AV	Market share of the financial advisor in the particular year, retrieved annually from the M&A league table.	**Eikon**
Acquirer controls		
SIZE_AQ	Size of the acquirer measured in total assets.	**Thomson**
EXP_AQ	Experience of the acquirer measured as the number of deals executed by the acquirer at the current transaction, during the observation period.	**Thomson**
Target controls		

EXP_TA	Experience of the target measured as the number of deals executed by the target at the current transaction, during the observation period.	**Thomson**
Deal specific controls		
DEALV	Deal value of the transaction measured in million dollars.	**Thomson**
PERC	Percentage of shares owned after the M&A transaction.	**Thomson**
NUMB	Variable which counts the amount of bidders within a transaction.	**Thomson**
CRB	Dummy variable which is equal to one when the target firm is located in another country than the acquirer firm.	**Thomson**
ATT	Dummy variable which is equal to 1 when the transaction is a friendly takeover and equal to 0 otherwise.	**Thomson**
CASH	Reflects the percentage of the transaction which is paid in cash.	**Thomson**
SICSAME	Dummy variable which is equal to 1 when the industry SIC-code of target is the same as the industry SIC-code of the acquirer.	**Thomson**
NUM_AQAV	Number of acquirer advisors involved in the current transaction.	**Thomson**
Country & year specific controls		
YEAR FE	Year fixed effects: 10 dummy variables for the years 2009 – 2018.	**Thomson**
COUNTRY FE	Country fixed effects: 31 dummy variables for the nationality of the acquiring company.	**Thomson**

Table 3 represents the description of all variables in the analyses. Please note that the variables *REP_AV*, *EXP_AV*, *MASH_AV* all relate to the advisors in the current transaction. The same variable descriptions hold for *REP_MAV*, *EXP_MAV*, *MASH_MAV*, but these variables are related to the main advisor and not to the advisor in the current transaction.

Appendix B

TABLE 4: BREUSCH-PAGAN / COOK-WEISBERG TEST FOR HETEROSKEDASTICITY

H_o: Constant variance	
Chi2	289.43
Prob > chi2	0.0000
Reject H_o	YES

Table 4 represents the test results of the Breusch-Pagan test.

Appendix C

TABLE 5: DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std.Dev.	Min	Max
CAR1	1352	1.64	6.64	-34.03	79.46
D	1352	.19	.35	0	1
SWITCH	1352	.29	.45	0	1
REP_AV	1352	90.6	133.63	1	500
EXP_AV	1352	49.09	40.49	0	157
MASH_AV	1352	8.95	11	0	45.2
log_SIZE_AQ	1314	7.09	2.77	-.9	12.67
log_DEALV	1160	4.66	2.46	-3.44	11.53
log_FEES_AV	1020	4.21	2.23	-3.44	10.15
EXP_AQ	1352	1.02	2	0	19
EXP_TG	1352	.04	.24	0	3
PERC	1352	95.86	11.79	50	100
CRB	1352	.55	.5	0	1
SICSAME	1352	.39	.49	0	1
CASH	1352	39.35	44.31	0	100
ATT	1352	.98	.15	0	1
NUMB	1352	1.01	.11	1	3
NUM_AQAV	1352	1.38	.82	1	7

Table 5 represents the descriptive statistics for each variable. It reports the number of observations, the mean, the standard deviation, the minimum and the maximum value of each variable.

Appendix D

TABLE 6: SUMMARY STATISTICS PER ADVISOR

		Ranking (REP_AV)			Marketshare % (MASH_AV)			Number of deals (EXP_AV)		
	Advisor	**Min**	**Max**	**Average**	**Min**	**Max**	**Average**	**Min**	**Max**	**Average**
1	Goldman Sachs & Co	1.0	6.0	1.5	22.3	45.2	32.4	78.0	120.0	102.9
2	Morgan Stanley	1.0	5.0	2.7	15.9	42.4	26.4	66.0	136.0	99.3
3	Deutsche Bank	1.0	10.0	4.5	12.2	29.5	21.7	44.0	112.0	81.1
4	JP Morgan	2.0	10.0	4.6	13.1	39.2	23.7	73.0	115.0	97.9
5	Credit Suisse	3.0	12.0	6.9	7.6	25.0	17.4	44.0	103.0	76.4
6	Citi	4.0	12.0	7.1	9.1	25.3	17.6	44.0	79.0	67.3
7	Lazard	3.0	14.0	7.7	9.3	37.1	18.9	106.0	157.0	128.3
8	Bank of America Merrill Lynch	2.0	15.0	8.1	9.6	39.4	18.1	49.0	75.0	64.2
9	UBS	4.0	17.0	9.2	5.3	23.2	15.0	57.0	103.0	80.3
10	Barclays	3.0	19.0	9.6	4.2	27.9	15.8	23.0	69.0	54.9
11	BNP Paribas SA	8.0	22.0	11.6	5.0	19.9	12.9	75.0	110.0	93.6
12	HSBC Holdings PLC	13.0	19.0	14.5	4.5	10.3	7.0	24.0	58.0	36.1
13	Societe Generale	10.0	25.0	14.8	2.1	13.3	6.9	28.0	95.0	60.1
14	Credit Agricole CIB	10.0	33.0	21.6	2.2	11.0	5.4	38.0	60.0	47.8
15	Mediobanca	12.0	32.0	21.6	1.6	8.0	4.0	31.0	52.0	42.3
16	VTB Capital	18.0	27.0	23.3	2.0	3.5	3.0	9.0	20.0	15.3
17	RBS	17.0	34.0	25.1	1.8	5.6	3.5	20.0	42.0	32.3
18	Nomura	11.0	35.0	26.3	1.2	13.3	3.5	21.0	60.0	32.5
19	Guggenheim Securities LLC	27.0	27.0	27.0	2.2	2.2	2.2	5.0	5.0	5.0
20	Santander Corp & Invest Bkg	16.0	89.0	32.0	0.2	5.6	2.7	15.0	28.0	19.4
21	Jefferies LLC	17.0	47.0	32.1	0.7	5.0	1.8	23.0	43.0	32.6
22	Banca IMI (Intesa Sanpaolo)	18.0	48.0	33.8	0.9	4.6	2.0	26.0	51.0	33.3
23	RBC Capital Markets	29.0	55.0	34.4	0.7	2.1	1.7	11.0	19.0	16.6
24	Renaissance Capital Group	35.0	35.0	35.0	1.8	1.8	1.8	16.0	16.0	16.0
25	Nordea	27.0	77.0	37.2	0.2	2.9	1.7	16.0	24.0	21.0
26	SEB	24.0	49.0	38.6	0.9	2.7	1.6	16.0	43.0	32.3
27	UniCredit	18.0	67.0	41.1	0.4	5.2	1.7	34.0	64.0	52.9
28	ING	16.0	97.0	51.8	0.2	5.8	1.4	26.0	60.0	38.4
29	Sberbank CIB	26.0	95.0	55.2	0.2	2.6	1.4	10.0	31.0	22.0
30	Macquarie Group	26.0	97.0	55.7	0.2	3.3	1.5	20.0	33.0	24.7
31	NIBC NV	24.0	92.0	58.0	0.1	2.4	1.3	12.0	13.0	12.5
32	BMO Capital Markets	38.0	73.0	58.4	0.3	1.0	0.6	3.0	10.0	6.3
33	BBVA	53.0	70.0	61.0	0.2	0.7	0.5	11.0	19.0	16.0
34	Kempen and Co NV	33.0	88.0	61.3	0.2	1.5	0.7	6.0	11.0	8.7
35	Numis	33.0	161.0	61.4	0.0	1.5	0.6	4.0	30.0	20.4
36	Natixis	23.0	121.0	61.6	0.1	2.7	0.9	9.0	55.0	30.3
37	Handelsbanken Capital Markets	20.0	133.0	62.4	0.1	2.9	1.0	11.0	17.0	14.5
38	Carnegie	43.0	118.0	67.6	0.1	1.0	0.6	11.0	30.0	24.5
39	ABN AMRO Bank	47.0	101.0	68.8	0.1	0.9	0.5	2.0	17.0	9.5
40	Canaccord Genuity	32.0	94.0	70.0	0.1	1.7	0.4	19.0	36.0	26.7
41	Cooperatieve Rabobank UA	30.0	133.0	70.9	0.1	2.1	0.7	41.0	58.0	48.8
42	Rand Merchant Bank	72.0	72.0	72.0	0.3	0.3	0.3	3.0	3.0	3.0
43	Equita SIM SpA	73.0	73.0	73.0	0.2	0.2	0.2	3.0	3.0	3.0
44	CIBC World Markets Inc	74.0	74.0	74.0	0.4	0.4	0.4	7.0	7.0	7.0

45	Investec	46.0	149.0	74.6	0.0	0.9	0.4	9.0	21.0	15.2
46	Danske Bank	49.0	97.0	75.0	0.1	0.8	0.4	10.0	35.0	23.0
47	Seymour Pierce	75.0	75.0	75.0	0.2	0.2	0.2	12.0	12.0	12.0
48	William Blair & Co	54.0	93.0	77.3	0.1	0.4	0.2	6.0	18.0	14.0
49	Arctic Securities ASA	68.0	118.0	79.7	0.1	0.4	0.3	6.0	21.0	12.0
50	First Securities AS	82.0	83.0	82.5	0.2	0.3	0.3	9.0	10.0	9.5
51	Scotiabank	83.0	83.0	83.0	0.2	0.2	0.2	3.0	3.0	3.0
52	ABG Sundal Collier	51.0	154.0	83.7	0.0	0.8	0.4	9.0	19.0	14.8
53	Piper Jaffray Cos	80.0	91.0	83.7	0.1	0.3	0.2	12.0	18.0	16.0
54	Peel Hunt LLP	85.0	95.0	88.3	0.1	0.2	0.2	8.0	13.0	11.3
55	Grant Thornton	50.0	147.0	95.8	0.1	0.7	0.3	43.0	114.0	79.2
56	DNB ASA	54.0	236.0	99.5	0.0	0.6	0.4	4.0	21.0	12.2
57	Landesbank Baden-Wurttemberg	108.0	108.0	108.0	0.1	0.1	0.1	4.0	4.0	4.0
58	Swedbank	85.0	160.0	113.0	0.0	0.2	0.1	5.0	12.0	8.5
59	Stifel/KBW	111.0	118.0	116.3	0.1	0.1	0.1	10.0	12.0	10.5
60	Clarksons Platou Securities AS	66.0	178.0	122.0	0.0	0.4	0.2	1.0	1.0	1.0
61	Standard Chartered PLC	126.0	126.0	126.0	0.1	0.1	0.1	1.0	1.0	1.0
62	FirstEnergy Capital Corp	129.0	129.0	129.0	0.1	0.1	0.1	4.0	4.0	4.0
63	Cenkos Securities PLC	58.0	217.0	131.9	0.0	0.4	0.1	5.0	23.0	18.0
64	Berenberg Bank	47.0	276.0	145.2	0.0	0.7	0.3	3.0	9.0	6.2
65	Banco Espirito Santo SA	28.0	500.0	146.0	0.0	2.6	2.0	0.0	45.0	33.8
66	Evolution Group	151.0	151.0	151.0	0.1	0.1	0.1	5.0	5.0	5.0
67	SunTrust Banks	151.0	151.0	151.0	0.0	0.0	0.0	1.0	1.0	1.0
68	Commerzbank AG	51.0	218.0	158.5	0.0	0.6	0.2	8.0	18.0	11.0
69	Bryan Garnier & Co	131.0	231.0	162.7	0.0	0.1	0.1	14.0	25.0	22.5
70	Shore Capital Group	60.0	191.0	164.5	0.0	0.5	0.1	7.0	9.0	8.1
71	JM Financial Group	166.0	166.0	166.0	0.0	0.0	0.0	4.0	4.0	4.0
72	Merchant Securities Ltd	168.0	168.0	168.0	0.0	0.0	0.0	11.0	11.0	11.0
73	Oddo BHF SCA	121.0	198.0	170.3	0.0	0.1	0.0	9.0	14.0	11.2
74	Avanza AB	180.0	180.0	180.0	0.0	0.0	0.0	2.0	2.0	2.0
75	Liberum Capital	113.0	227.0	181.7	0.0	0.1	0.0	2.0	26.0	13.6
76	GMP Capital Corp	59.0	321.0	183.0	0.0	0.5	0.2	1.0	4.0	2.7
77	finnCap Ltd	131.0	249.0	185.0	0.0	0.1	0.0	3.0	19.0	12.8
78	RS Platou Markets AS	186.0	186.0	186.0	0.0	0.0	0.0	2.0	2.0	2.0
79	Stockdale Securities Ltd	109.0	341.0	186.3	0.0	0.1	0.1	5.0	7.0	6.3
80	Pareto AS	194.0	194.0	194.0	0.0	0.0	0.0	4.0	4.0	4.0
81	Brewin Dolphin	199.0	199.0	199.0	0.0	0.0	0.0	12.0	12.0	12.0
82	Ahorro Corporacion Financiera	202.0	202.0	202.0	0.0	0.0	0.0	4.0	4.0	4.0
83	IKB Deutsche Industriebank	202.0	202.0	202.0	0.0	0.0	0.0	6.0	6.0	6.0
84	Aurel BGC SASU	141.0	270.0	205.5	0.0	0.1	0.1	1.0	1.0	1.0
85	Goodbody Corporate Finance	161.0	276.0	211.3	0.0	0.0	0.0	4.0	7.0	5.3
86	N1 Singer Ltd	143.0	500.0	213.6	0.0	0.1	0.0	0.0	14.0	11.0
87	KBC Group NV	211.0	217.0	214.0	0.0	0.0	0.0	5.0	23.0	14.0
88	Fondsfinans AS	216.0	216.0	216.0	0.0	0.0	0.0	2.0	2.0	2.0
89	Daniel Stewart	217.0	287.0	240.3	0.0	0.0	0.0	1.0	6.0	4.3
90	Charles Stanley	125.0	298.0	240.5	0.0	0.1	0.0	1.0	7.0	4.2
91	Cantor Fitzgerald Europe	219.0	247.0	242.3	0.0	0.0	0.0	7.0	7.0	7.0
92	Alpha Corporate Finance	229.0	274.0	244.0	0.0	0.0	0.0	4.0	6.0	5.3
93	WH Ireland Ltd	188.0	321.0	248.5	0.0	0.0	0.0	4.0	15.0	8.5
94	Evli Bank Plc	228.0	276.0	252.0	0.0	0.0	0.0	2.0	6.0	4.0
95	Erik Penser	185.0	327.0	256.0	0.0	0.0	0.0	1.0	2.0	1.5

96	Nord/LB	261.0	261.0	261.0	0.0	0.0	0.0	1.0	1.0	1.0
97	Oriel Securities Limited	228.0	304.0	266.0	0.0	0.0	0.0	1.0	2.0	1.5
98	Beaumont Cornish	246.0	289.0	267.5	0.0	0.0	0.0	4.0	4.0	4.0
99	Kepler Capital Markets	219.0	337.0	278.0	0.0	0.0	0.0	2.0	4.0	3.0
100	Davy Corp plc	276.0	304.0	279.5	0.0	0.0	0.0	1.0	4.0	3.6
101	Atout Capital	264.0	368.0	290.0	0.0	0.0	0.0	3.0	6.0	5.3
102	Banca Profilo SpA	294.0	294.0	294.0	0.0	0.0	0.0	1.0	1.0	1.0
103	E Ohman Jr Fondkommission	294.0	303.0	298.5	0.0	0.0	0.0	1.0	1.0	1.0
104	Dom Inwestycyjny Investors SA	301.0	301.0	301.0	0.0	0.0	0.0	2.0	2.0	2.0
105	Libertas Capital Group Plc	302.0	302.0	302.0	0.0	0.0	0.0	3.0	3.0	3.0
106	John East & Partners Ltd	310.0	310.0	310.0	0.0	0.0	0.0	2.0	2.0	2.0
107	DENIZ YATIRIM MENKUL KIYMETLER	331.0	331.0	331.0	0.0	0.0	0.0	1.0	1.0	1.0
108	Astaire Securities PLC	335.0	335.0	335.0	0.0	0.0	0.0	3.0	3.0	3.0
109	FOX DAVIES CAPITAL	306.0	374.0	340.0	0.0	0.0	0.0	1.0	2.0	1.5
110	Arden Partners Ltd	360.0	360.0	360.0	0.0	0.0	0.0	4.0	4.0	4.0
111	Maxim Group LLC	363.0	363.0	363.0	0.0	0.0	0.0	1.0	1.0	1.0
112	SVS Securities Plc	382.0	382.0	382.0	0.0	0.0	0.0	2.0	2.0	2.0
113	Religare Capital Markets Ltd	387.0	387.0	387.0	0.0	0.0	0.0	1.0	1.0	1.0
114	Sanlam Ltd	388.0	388.0	388.0	0.0	0.0	0.0	3.0	3.0	3.0
115	Greentech Capital Advisors	403.0	403.0	403.0	0.0	0.0	0.0	1.0	1.0	1.0
116	Smith & Williamson Group	405.0	410.0	408.3	0.0	0.0	0.0	1.0	5.0	3.3
117	Midcap Partners SAS	409.0	409.0	409.0	0.0	0.0	0.0	1.0	1.0	1.0
118	SP Angel & Co	405.0	500.0	436.7	0.0	0.0	0.0	0.0	1.0	0.7
119	Northland Securities Group LLC	285.0	500.0	457.0	0.0	0.0	0.0	0.0	2.0	0.4
120	Allenby Capital	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
121	GCA Altium	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
122	RFC Ambrian	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
123	Arbuthnot Bankcing Group PLC	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
124	Banco Itau BBA S.A.	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
125	BRE Corporate Finance SA	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
126	Caixa Geral de Depositos	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
127	Calyon	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
128	Crédit Industriel et Commercial	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
129	Close Brothers Group	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
130	CM-CIC Investissement	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
131	Collins Stewart Tullett	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
132	Degroof Petercam - IMAP	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
133	Trigon Dom Maklerski SA	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
134	Dowgate Capital Stockbrokers	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
135	Execution Noble	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
136	Fairfax IS PLC	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
137	Is Yatirim Menkul Degerler	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
138	Mirabaud Securities Limited	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
139	Mitsubishi UFJ	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
140	Nmas1	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
141	Panmure Gordon & Co Ltd	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
142	Sal Oppenheim	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
143	N+1 Singer Capital Markets Ltd	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
144	Troika Dialog	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
145	Ulster Bank Ltd	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0

146	Westhouse Holdings PLC	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
147	Zeus Capital Ltd	500.0	500.0	500.0	0.0	0.0	0.0	0.0	0.0	0.0
	Average			90.6			8.9			49.1

Table 6 reports the summary statistics for each advisor in the dataset. It reports the minimum value, the maximum value and the average for the variables *REP_AV, MASH_AV and EXP_AV*.

Appendix E

TABLE 7: ACQUIRERS' NATION AND FREQUENCY

Country_AQ	Freq.	Percent	Cum.
Austria	8	0.59	0.59
Belgium	27	2.00	2.59
Croatia	1	0.07	2.66
Cyprus	4	0.30	2.96
Denmark	16	1.18	4.14
Estonia	1	0.07	4.22
Faroe Islands	2	0.15	4.36
Finland	24	1.78	6.14
France	213	15.75	21.89
Germany	95	7.03	28.92
Gibraltar	1	0.07	28.99
Greece	4	0.30	29.29
Ireland-Rep	51	3.77	33.06
Isle of Man	3	0.22	33.28
Italy	73	5.40	38.68
Jersey	4	0.30	38.98
Luxembourg	5	0.37	39.35
Malta	1	0.07	39.42
Monaco	1	0.07	39.50
Netherlands	53	3.92	43.42
Norway	47	3.48	46.89
Poland	14	1.04	47.93
Portugal	5	0.37	48.30
Russian Fed	42	3.11	51.41
Slovenia	1	0.07	51.48
Spain	49	3.62	55.10
Sweden	91	6.73	61.83
Switzerland	69	5.10	66.94
Turkey	6	0.44	67.38
Ukraine	1	0.07	67.46
United Kingdom	440	32.54	100.00

Table 7 reports the number of observations per acquirers' nation and the percentage and cumulative size in the dataset.

Appendix F

TABLE 8: FOUR QUANTILES REPUTATION M&A ADVISOR AND LOCK-IN STATISTICS

4 quantiles *REP_AV*	Mean	Standard Deviation	Frequency
1	.06788673	.18054362	352
2	.1156831	.25882858	336
3	.24928773	.40055992	344
4	.32012029	.43581991	320
Total	.18562065	.34757675	1,352

Four different subsamples of M&A advisors regarding their reputation (*REP_AV*). The average statistics for the variable lock-in (*D)* is given for every subsample.

TABLE 9: FOUR QUANTILES REPUTATION M&A ADVISOR AND REPUTATION STATISTICS

4 quantiles REP_AV	Mean	Standard Deviation	Frequency
1	3.9119318	2.0410809	352
2	14.907738	6.5586083	336
3	65.479651	24.541026	344
4	292.4375	138.05465	320
Total	90.599852	133.63317	1,352

Four different subsamples of M&A advisors regarding their reputation (*REP_AV*). The average statistics for the variable reputation (*REP_AV)* is given for every subsample.

Appendix G

TABLE 10: PEARSON'S CORRELATION MATRIX

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) CAR1	1.000																	
(2) D	-0.004	1.000																
(3) SWITCH	-0.052	-0.190*	1.000															
(4) REP_AV	0.033	0.215*	-0.169*	1.000														
(5) EXP_AV	-0.054	-0.276*	0.216*	-0.628*	1.000													
(6) MASH_AV	-0.042	-0.242*	0.199*	-0.512*	0.810*	1.000												
(7) log_SIZE_AQ	-0.148*	-0.326*	0.351*	-0.539*	0.541*	0.541*	1.000											
(8) log_DEALV	-0.011	-0.371*	0.244*	-0.573*	0.528*	0.585*	0.711*	1.000										
(9) log_FEES_AV	-0.003	-0.347*	0.212*	-0.565*	0.501*	0.545*	0.677*	0.998*	1.000									
(10) EXP_AQ	-0.048	0.216*	0.116*	-0.055	0.024	-0.001	0.102*	-0.061	-0.085*	1.000								
(11) EXP_TG	-0.031	-0.040	0.032	-0.054	0.052	0.036	0.142*	-0.015	-0.010	0.146*	1.000							
(12) PERC	0.006	0.079*	-0.073*	0.057	-0.044	-0.030	-0.203*	-0.044	-0.030	0.014	-0.050	1.000						
(13) CRB	-0.033	-0.233*	0.161*	-0.293*	0.300*	0.299*	0.374*	0.424*	0.428*	-0.030	0.006	-0.062	1.000					
(14) SICSAME	-0.016	-0.022	-0.003	0.035	-0.031	-0.041	-0.028	0.025	0.015	-0.070*	-0.019	-0.029	0.044	1.000				
(15) CASH	-0.009	-0.015	0.039	-0.117*	0.059	0.101*	0.092*	0.150*	0.142*	-0.026	0.115*	0.042	0.092*	-0.031	1.000			
(16) ATT	0.033	0.033	-0.004	0.046	-0.040	-0.016	-0.085*	-0.030	-0.056	-0.008	-0.016	0.108*	-0.027	-0.012	-0.039	1.000		
(17) NUMB	-0.034	0.001	0.003	-0.044	0.016	0.029	0.034	0.070	0.050	-0.011	0.042	-0.008	0.024	-0.028	0.041	0.014	1.000	
(18) NUM_AQAV	-0.035	-0.122*	0.134*	-0.167*	0.198*	0.231*	0.225*	0.403*	0.145*	-0.028	0.006	-0.053	0.082*	0.048	0.050	0.026	0.082*	1.000

Table 10 reports the Pearson's Correlation matrix for all the variables. * shows significance at the .01 level

Appendix H

TABLE 11: VARIANCE INFLATION FACTOR

VARIABLE	VIF	1/VIF
log_DEALV	204.321	.005
log_FEES_AV	202.784	.005
EXP_AV	3.788	.264
MASH_AV	3.413	.293
log_SIZE_AQ	2.567	.39
REP_AV	1.97	.508
D	1.331	.751
CRB	1.294	.773
EXP_AQ	1.19	.84
SWITCH	1.151	.868
PERC	1.124	.89
EXP_TG	1.094	.914
CASH	1.052	.951
NUM_AQAV	1.048	.954
ATT	1.044	.958
SICSAME	1.026	.975
NUMB	1.017	.983
Mean VIF	25.366	.

Table 11 reports the variable inflation factors for all explanatory variables.

TABLE 12: VARIANCE INFLATION FACTOR WITHOUT LOG_FEES_AV

VARIABLE	ViF	1/VIF
EXP_AV	3.687	.271
MASH_AV	3.423	.292
log_DEALV	3.018	.331
log SIZE_AQ	2.792	.358
REP_AV	1.979	.505
D	1.342	.745
CRB	1.282	.78
NUM_AQAV	1.245	.803
EXP_AQ	1.176	.85
SWITCH	1.176	.85
PERC	1.113	.898
EXP_TG	1.088	.919
CASH	1.052	.95
ATT	1.035	.966
SICSAME	1.027	.973
NUMB	1.015	.986
Mean VIF	1.716	.

Table 12 reports the variable inflation factors for all explanatory variables except *log_FEES_AV*.

Appendix I

TABLE 13: OLS REGRESSION RESULTS ON CUMULATIVE ABNORMAL RETURNS (-1, +1)

Variables	(1) Full sample	(2) Full sample	(3) Top-Tier	(4) Top-Tier	(5) Low-Tier	(6) Low-Tier
D	-0.307	-0.239	-1.456	-2.473	0.641	0.831
	(0.613)	(0.643)	(2.176)	(2.645)	(1.143)	(1.329)
REP_AV	-0.00223	-0.00167	-0.0521	-0.0103	0.00601	0.00917*
	(0.00195)	(0.00208)	(0.191)	(0.353)	(0.00364)	(0.00431)
EXP_AV	-0.00107	-0.00326	0.00204	-0.0196	0.0793+	0.0922*
	(0.00806)	(0.00895)	(0.0137)	(0.0189)	(0.0456)	(0.0459)
MASH_AV	0.00641	0.0239	0.0731	0.129	4.119	12.16
	(0.0287)	(0.0321)	(0.0663)	(0.154)	(16.19)	(18.14)
log_SIZE_AQ	-0.607***	-0.701***	-0.817**	-1.030***	-0.377+	-0.497+
	(0.107)	(0.120)	(0.260)	(0.292)	(0.223)	(0.261)
log_DEALV	0.450***	0.441***	0.613+	0.751*	0.273	0.342
	(0.119)	(0.124)	(0.331)	(0.362)	(0.330)	(0.376)
EXP_AQ	-0.0518	-0.00981	-0.0462	0.104	0.175	0.153
	(0.0549)	(0.0671)	(0.183)	(0.248)	(0.201)	(0.265)
EXP_TG	0.111	0.0964	0.297	-0.0404	-2.600*	-3.510*
	(0.386)	(0.471)	(0.736)	(0.881)	(1.292)	(1.373)
PERC	-0.0244*	-0.0219*	-0.0452+	-0.0310	-0.0340	-0.0643
	(0.0111)	(0.0109)	(0.0234)	(0.0259)	(0.0385)	(0.0498)
CRB	-0.0765	-0.293	0.697	-0.0955	0.850	-0.169
	(0.390)	(0.430)	(0.719)	(0.844)	(1.259)	(1.684)
SICSAME	-0.0560	0.0452	-0.778	-0.624	-0.263	0.104
	(0.371)	(0.387)	(0.717)	(0.776)	(0.896)	(1.015)
CASH	-0.000492	0.000640	-0.00556	-0.00513	0.00235	0.00591
	(0.00396)	(0.00411)	(0.00705)	(0.00710)	(0.0110)	(0.0126)
ATT	1.129	1.092	0.654	-0.0638	1.634	2.725
	(0.689)	(0.765)	(1.112)	(1.933)	(1.544)	(2.800)
NUMB	-2.075***	-1.898***	-1.764	-1.722		
	(0.395)	(0.488)	(1.113)	(1.095)		
NUM_AQAV	-0.301	-0.299	-0.125	-0.184	0.115	-0.241
	(0.229)	(0.242)	(0.413)	(0.426)	(1.221)	(1.405)
Constant	7.898***	5.115**	8.588*	10.80	1.104	-0.671
	(1.543)	(1.922)	(4.027)	(6.739)	(4.418)	(6.115)
Observations	1,127	1,127	314	314	246	246
R-squared	0.039	0.070	0.073	0.188	0.035	0.110
Country FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes

Table 13 presents the OLS regressions on *CAR (-1,+1)*. Model 1 and 2 include the full sample with and without year and country fixed effects. Model 3 and 4 represent a subsample which only includes deals advised by the top-ranked 25% advisors, with and without year and country fixed effects. Model 5 and 6 represent a subsample which only includes deals advised by the lowest ranked 25% advisors, with and without year and country fixed effects. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

TABLE 14: OLS REGRESSION RESULTS ON CUMULATIVE ABNORMAL RETURNS (-5, +5)

VARIABLES	(1) Full sample	(2) Top-Tier	(3) Low-Tier
D	-0.370	0.734	0.572
	(1.045)	(3.297)	(2.006)
REP_AV	-0.00320	0.618	0.00980
	(0.00351)	(0.448)	(0.00773)
EXP_AV	0.00348	-0.0101	0.0353
	(0.0124)	(0.0219)	(0.0706)
MASH_AV	-0.0273	0.273	17.10
	(0.0420)	(0.195)	(24.62)
log_SIZE_AQ	-0.797***	-0.998**	-0.771
	(0.184)	(0.372)	(0.549)
log_DEALV	0.693***	0.765+	0.981+
	(0.186)	(0.424)	(0.570)
EXP_AQ	-0.159	0.211	0.0324
	(0.121)	(0.305)	(0.373)
EXP_TG	0.218	0.211	-7.061
	(0.650)	(1.064)	(7.726)
PERC	-0.0273+	-0.0163	0.00398
	(0.0161)	(0.0297)	(0.0731)
CRB	0.345	0.201	0.0818
	(0.575)	(1.190)	(2.095)
SICSAME	-0.402	-0.960	0.521
	(0.534)	(1.006)	(1.559)
CASH	0.00119	-0.00115	0.00409
	(0.00560)	(0.00912)	(0.0183)
ATT	0.842	-0.409	11.26
	(1.167)	(1.895)	(10.55)
NUMB	-0.832	0.667	
	(1.099)	(2.079)	
NUM_AQAV	-0.445	-0.303	-0.0218
	(0.316)	(0.535)	(2.340)
Constant	2.310	1.280	-10.31
	(3.478)	(7.969)	(13.77)
Observations	1,127	314	246
R-squared	0.058	0.167	0.134
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 14 presents the OLS regressions on *CAR (-5,+5)*. Model 1 reflects the full sample. Model 2 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 3 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

TABLE 15: OLS REGRESSION RESULTS ON CAR (-1, +1) INCLUDING FEES

VARIABLES	(1) Full sample	(2) Top-Tier	(3) Low-Tier
D	-0.0491	-1.513	0.843
	(0.648)	(2.786)	(1.333)
REP_AV	-0.00110	0.0973	0.00906*
	(0.00212)	(0.429)	(0.00446)
EXP_AV	-0.00708	-0.0204	0.0903+
	(0.00974)	(0.0201)	(0.0473)
MASH_AV	0.0439	0.200	13.20
	(0.0361)	(0.192)	(18.72)
log_SIZE_AQ	-0.633***	-0.849**	-0.471+
	(0.124)	(0.316)	(0.270)
log_FEES_AV	0.394**	1.001*	0.268
	(0.134)	(0.454)	(0.380)
EXP_AQ	0.0211	0.354	0.144
	(0.0680)	(0.250)	(0.264)
EXP_TG	-0.145	-0.155	-3.603**
	(0.484)	(0.959)	(1.377)
PERC	-0.0147	-0.0236	-0.0600
	(0.0117)	(0.0285)	(0.0517)
CRB	-0.325	-0.401	-0.154
	(0.465)	(1.055)	(1.745)
SICSAME	-0.101	-1.213	0.101
	(0.413)	(0.884)	(1.029)
CASH	0.00570	7.80e-05	0.00646
	(0.00440)	(0.00869)	(0.0125)
ATT	0.877	-2.666*	2.783
	(0.814)	(1.348)	(2.878)
NUMB	-1.688*	-0.852	
	(0.665)	(2.000)	
NUM_AQAV	-0.182	0.177	-0.207
	(0.384)	(0.834)	(1.415)
Constant	3.977+	6.041	-0.897
	(2.165)	(7.795)	(6.260)
Observations	988	232	243
R-squared	0.062	0.187	0.107
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 15 presents the OLS regressions on *CAR (-1, +1)*. The variable *log_DEALV* is left out and *log_FEES_AV* is included. Model 1 represents the full sample. Model 2 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 3 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

TABLE 16: OLS REGRESSION RESULTS ON CAR (-1,+1) WITH DIFFERENT MEASUREMENTS LOCK-IN

VARIABLES	(1) Full sample	(2) Full sample	(3) Top-Tier	(4) Top-Tier	(5) Low-Tier	(6) Low-Tier
D_5	-0.269		-0.222		0.854	
	(0.435)		(0.968)		(1.221)	
D_2000		-0.280		-0.209		0.447
		(0.397)		(0.831)		(1.182)
REP_AV	-0.00171	-0.00176	-0.0196	-0.0202	0.00940*	0.00940*
	(0.00208)	(0.00208)	(0.352)	(0.352)	(0.00430)	(0.00426)
EXP_AV	-0.00362	-0.00388	-0.0170	-0.0172	0.0937*	0.0921*
	(0.00898)	(0.00895)	(0.0193)	(0.0192)	(0.0459)	(0.0451)
MASH_AV	0.0253	0.0257	0.122	0.122	12.39	12.05
	(0.0320)	(0.0320)	(0.155)	(0.155)	(18.25)	(18.14)
log_SIZE_AQ	-0.700***	-0.697***	-0.987***	-0.984***	-0.488+	-0.492+
	(0.119)	(0.119)	(0.290)	(0.289)	(0.262)	(0.260)
log_DEALV	0.438***	0.441***	0.745*	0.749*	0.350	0.334
	(0.124)	(0.123)	(0.361)	(0.361)	(0.378)	(0.377)
EXP_AQ	-0.00738	-0.00782	0.0997	0.0993	0.143	0.175
	(0.0654)	(0.0652)	(0.248)	(0.248)	(0.264)	(0.271)
EXP_TG	0.109	0.107	0.0188	0.0179	-3.482*	-3.582*
	(0.466)	(0.466)	(0.872)	(0.874)	(1.397)	(1.422)
PERC	-0.0222*	-0.0223*	-0.0318	-0.0313	-0.0632	-0.0639
	(0.0109)	(0.0109)	(0.0256)	(0.0260)	(0.0502)	(0.0501)
CRB	-0.308	-0.313	2.30e-05	0.0113	-0.196	-0.264
	(0.430)	(0.433)	(0.852)	(0.866)	(1.688)	(1.699)
SICSAME	0.0529	0.0589	-0.659	-0.665	0.118	0.135
	(0.388)	(0.388)	(0.785)	(0.785)	(1.005)	(0.999)
CASH	0.000636	0.000629	-0.00546	-0.00556	0.00583	0.00576
	(0.00411)	(0.00411)	(0.00704)	(0.00704)	(0.0126)	(0.0126)
ATT	1.076	1.081	-0.119	-0.103	2.672	2.710
	(0.765)	(0.762)	(1.905)	(1.908)	(2.806)	(2.819)
NUMB	-1.845***	-1.830***	-1.582	-1.515		
	(0.501)	(0.494)	(1.090)	(1.120)		
NUM_AQAV	-0.296	-0.298	-0.166	-0.164	-0.265	-0.232
	(0.242)	(0.243)	(0.428)	(0.431)	(1.414)	(1.406)
Constant	5.133**	5.086**	9.345	9.191	-0.782	-0.721
	(1.921)	(1.917)	(6.752)	(6.585)	(6.147)	(6.132)
Observations	1,127	1,127	314	314	246	246
R-squared	0.070	0.070	0.183	0.183	0.110	0.109
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 16 presents the OLS regressions on *CAR (-1, +1)*. Different measurements of a potential lock-in are included. Model 1 and 2 represent the full sample. Model 3 and 4 represent a subsample which only includes deals advised by the top-ranked 25% advisors. Model 5 and 6 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

TABLE 17: OLS REGRESSION RESULTS ON CAR (-1,+1) ONLY LEAGUE TABLE OBSERVATIONS

VARIABLES	(1) Full sample	(2) Full sample	(3) Full sample	(4) Top-Tier	(5) Low-Tier
D			-0.306	-2.473	1.377
			(0.683)	(2.645)	(1.764)
REP_AV		-0.00810*	-0.00815*	-0.0103	0.0139
		(0.00363)	(0.00364)	(0.353)	(0.0111)
EXP_AV	0.00120	-0.00640	-0.00678	-0.0196	0.0872+
	(0.00857)	(0.00896)	(0.00902)	(0.0189)	(0.0483)
MASH_AV	0.0178	0.0206	0.0212	0.129	17.60
	(0.0324)	(0.0324)	(0.0324)	(0.154)	(21.69)
log_SIZE_AQ	-0.640***	-0.684***	-0.689***	-1.030***	-0.137
	(0.122)	(0.124)	(0.125)	(0.292)	(0.338)
log_DEALV	0.427***	0.360**	0.353**	0.751*	-0.0740
	(0.126)	(0.126)	(0.128)	(0.362)	(0.477)
EXP_AQ	-0.0199	-0.0350	-0.0247	0.104	0.0328
	(0.0632)	(0.0632)	(0.0679)	(0.248)	(0.294)
EXP_TG	0.0560	0.0827	0.0648	-0.0404	-4.045*
	(0.479)	(0.482)	(0.485)	(0.881)	(1.569)
PERC	-0.0180+	-0.0193+	-0.0188+	-0.0310	-0.0447
	(0.0107)	(0.0106)	(0.0107)	(0.0259)	(0.0665)
CRB	-0.376	-0.457	-0.480	-0.0955	-0.621
	(0.438)	(0.435)	(0.437)	(0.844)	(2.115)
SICSAME	0.0970	0.0555	0.0531	-0.624	-0.136
	(0.393)	(0.390)	(0.390)	(0.776)	(1.241)
CASH	0.00103	0.000644	0.000678	-0.00513	0.00752
	(0.00419)	(0.00419)	(0.00421)	(0.00710)	(0.0147)
ATT	1.120	1.114	1.115	-0.0638	4.968
	(0.763)	(0.752)	(0.761)	(1.933)	(3.286)
NUMB	-1.792***	-1.895***	-1.872***	-1.722	
	(0.481)	(0.497)	(0.498)	(1.095)	
NUM_AQAV	-0.346	-0.313	-0.313	-0.184	-1.321
	(0.244)	(0.243)	(0.243)	(0.426)	(1.574)
Constant	4.337*	5.874**	5.954**	10.80	-1.833
	(1.833)	(1.939)	(1.955)	(6.739)	(7.617)
Observations	1,070	1,070	1,070	314	189
R-squared	0.069	0.074	0.074	0.188	0.123
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 17 presents the OLS regressions on *CAR (-1, +1)*. Observations where the advisor was not present in the top 500 league tables are removed from the regression analyses. Model 1 only incorporates control variables. Model 2 only incorporates *REP_AV* as main independent variable. Model 3 incorporates both *REP_AV* and *D* as main independent variables. Model 4 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 5 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Appendix J

TABLE 18: LOGISTIC REGRESSION RESULTS WITH AND WITHOUT FIXED EFFECTS

VARIABLES	(1) Full sample	(2) Full sample	(3) Top-Tier	(4) Top-Tier	(5) Low-Tier	(6) Low-Tier
D_MAV	0.508*	0.488*	1.367	0.790	0.247*	0.296*
	(0.147)	(0.137)	(1.055)	(0.501)	(0.176)	(0.178)
REP_MAV	1.002*	1.002*	1.178	1.064+	1.004*	1.002
	(0.000810)	(0.000786)	(0.128)	(0.0366)	(0.00196)	(0.00151)
MASH_MAV	0.998	0.988	1.038	0.958		
	(0.0129)	(0.0109)	(0.0669)	(0.0275)		
EXP_MAV	1.002	1.005	1.004	1.010	1.048**	1.028*
	(0.00371)	(0.00330)	(0.00715)	(0.00668)	(0.0181)	(0.0122)
log_SIZE_AQ	1.336***	1.327***	1.313*	1.331***	1.187	1.194
	(0.0727)	(0.0655)	(0.146)	(0.115)	(0.174)	(0.145)
log_DEALV	1.014	0.986	1.127	1.067	1.039	1.004
	(0.0576)	(0.0527)	(0.159)	(0.128)	(0.157)	(0.122)
EXP_AQ	1.159*	1.149*	1.601***	1.468**	1.156	1.141
	(0.0783)	(0.0750)	(0.225)	(0.191)	(0.177)	(0.165)
EXP_TG	0.786	0.707	0.503	0.392		1.469
	(0.249)	(0.213)	(0.301)	(0.345)		(1.405)
PERC	0.996	0.998	0.998	1.001	0.983	0.969+
	(0.00670)	(0.00629)	(0.0144)	(0.0143)	(0.0240)	(0.0159)
CRB	1.366	1.333	0.942	1.212	1.176	1.261
	(0.268)	(0.251)	(0.323)	(0.452)	(0.707)	(0.613)
SICSAME	1.120	1.123	1.040	1.021	1.561	1.447
	(0.188)	(0.179)	(0.323)	(0.306)	(0.668)	(0.560)
CASH	1.000	1.001	0.999	1.001	1.004	1.002
	(0.00168)	(0.00163)	(0.00322)	(0.00292)	(0.00447)	(0.00400)
ATT	1.588	1.588	1.901	2.137		
	(0.701)	(0.657)	(1.760)	(1.857)		
NUMB	0.672	0.881	0.163	0.225		
	(0.435)	(0.505)	(0.315)	(0.415)		
NUM_AQAV	1.186+	1.185+	1.420*	1.329*	0.772	0.728
	(0.121)	(0.110)	(0.234)	(0.180)	(0.385)	(0.319)
Constant	0.0328**	0.0221***	0.00744	0.0205	0.161	1.279
	(0.0430)	(0.0228)	(0.0229)	(0.0544)	(0.531)	(2.597)
Observations	1,097	1,127	302	314	222	242
Country FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No
Pseudo R	0.160	0.123	0.247	0.185	0.158	0.130
Wild Chi-square	159***	119.1***	148.4***	61.78***	41.74*	23.10*
Log-likelihood	-564.9	-599.3	-154.9	-173.7	-85.59	-98.46

Table 18 presents the logistic regressions on switching behavior, where the advisor characteristics are related to the main advisor. Model 1 and 2 include the full sample with and without year and country fixed effects. Model 3 and 4 represent a subsample which only includes deals advised by the top-ranked 25% advisors, with and without year and country fixed effects. Model 5 and 6 represent a subsample which only includes deals advised by the lowest ranked 25% advisors, with and without year and country fixed effects. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

TABLE 19: LOGISTIC REGRESSION RESULTS INCLUDING FEES

VARIABLES	(1) Full Sample	(2) Top-Tier	(3) Low-Tier
D_MAV	0.487*	0.890	0.250+
	(0.153)	(0.779)	(0.178)
REP_MAV	1.002+	1.226	1.004*
	(0.000819)	(0.160)	(0.00190)
MASH_MAV	1.004	1.083	
	(0.0146)	(0.0835)	
EXP_MAV	0.998	0.987	1.048**
	(0.00408)	(0.00905)	(0.0178)
log_SIZE_AQ	1.350***	1.284*	1.176
	(0.0788)	(0.163)	(0.180)
log_FEES_AV	1.036	1.326+	1.069
	(0.0601)	(0.206)	(0.164)
EXP_AQ	1.132+	1.633**	1.161
	(0.0769)	(0.299)	(0.176)
EXP_TG	0.785	0.385+	
	(0.280)	(0.223)	
PERC	0.996	0.990	0.983
	(0.00803)	(0.0166)	(0.0240)
CRB	1.409	0.897	1.162
	(0.296)	(0.370)	(0.695)
SICSAME	1.194	0.760	1.596
	(0.219)	(0.294)	(0.672)
CASH	0.998	0.994	1.004
	(0.00183)	(0.00410)	(0.00451)
ATT	1.373	0.757	
	(0.637)	(0.670)	
NUMB	0.479		
	(0.546)		
NUM_AQAV	1.243+	1.497	0.755
	(0.162)	(0.426)	(0.376)
Constant	0.0432*	0.00923	0.161
	(0.0678)	(0.0266)	(0.529)
Observations	957	223	221
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Pseudo R	0.146	0.291	0.157
Wild Chi-square	120.4***	106.5***	41.17*
Log-likelihood	-482.3	-104.8	-85.48

Table 19 presents the logistic regressions on switching behavior, where the advisor characteristics are related to the main advisor. The variable *log_DEALV* is left out and *log_FEES_AV* is included. Model 1 represents the full sample. Model 2 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 3 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

TABLE 20: LOGISTIC REGRESSION RESULTS WITH DIFFERENT MEASUREMENTS LOCK-IN

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Top-Tier	(4) Top-Tier	(5) Low-Tier	(6) Low-Tier
D_5MAV	0.778		1.179		0.320+	
	(0.168)		(0.493)		(0.194)	
D_2000MAV		0.726		1.371		0.269*
		(0.147)		(0.558)		(0.165)
REP_MAV	1.002*	1.002*	1.103**	1.107**	1.004*	1.004*
	(0.000872)	(0.000873)	(0.0341)	(0.0351)	(0.00183)	(0.00186)
MASH_MAV	1.011	1.011	1.086+	1.088+		
	(0.0156)	(0.0157)	(0.0488)	(0.0496)		
EXP_MAV	0.999	0.998	1.001	1.002	1.031	1.030
	(0.00441)	(0.00443)	(0.00875)	(0.00887)	(0.0211)	(0.0214)
log_SIZE_AQ	1.309***	1.312***	1.223+	1.227+	1.231	1.231
	(0.0773)	(0.0772)	(0.139)	(0.139)	(0.193)	(0.192)
log_DEALV	0.988	0.991	1.030	1.019	1.026	1.031
	(0.0614)	(0.0621)	(0.138)	(0.137)	(0.187)	(0.193)
EXP_AQ	1.067	1.068	1.441*	1.450*	1.143	1.159
	(0.0635)	(0.0632)	(0.223)	(0.222)	(0.171)	(0.175)
EXP_TG	0.842	0.836	0.674	0.666		
	(0.309)	(0.305)	(0.411)	(0.415)		
PERC	1.000	1.000	0.989	0.988	1.007	1.007
	(0.00761)	(0.00761)	(0.0148)	(0.0149)	(0.0321)	(0.0325)
CRB	1.445	1.421	0.951	0.953	1.622	1.838
	(0.324)	(0.319)	(0.394)	(0.390)	(1.059)	(1.229)
SICSAME	1.086	1.094	0.947	0.947	1.756	1.776
	(0.210)	(0.212)	(0.331)	(0.332)	(0.804)	(0.820)
CASH	1.001	1.001	1.000	1.000	1.004	1.005
	(0.00195)	(0.00194)	(0.00392)	(0.00388)	(0.00512)	(0.00523)
ATT	1.750	1.763	1.388	1.364		
	(0.972)	(0.997)	(1.261)	(1.210)		
NUMB	0.822	0.852	0.244	0.222		
	(0.506)	(0.514)	(0.447)	(0.414)		
NUM_AQAV	1.233+	1.229+	1.679**	1.694**	0.699	0.660
	(0.135)	(0.136)	(0.317)	(0.318)	(0.351)	(0.340)
Constant	0.0199**	0.0191**	0.0125	0.0123	0.0129	0.0141
	(0.0269)	(0.0258)	(0.0353)	(0.0346)	(0.0488)	(0.0536)
Observations	982	982	265	265	216	216
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R	0.132	0.133	0.220	0.222	0.139	0.146
Wild Chi-square	95.91***	95.83***	108.3***	109.2***	36.66+	36.34+
Log-likelihood	-479	-478.3	-133	-132.7	-78.01	-77.35

Table 20 presents the logistic regressions on switching behavior, where the advisor characteristics are related to the main advisor. Different measurements of a potential lock-in are included. Model 1 and 2 represent the full sample. Model 3 and 4 represent a subsample which only includes deals advised by the top-ranked 25% advisors. Model 5 and 6 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

TABLE 21: LOGISTIC REGRESSION RESULTS ONLY LEAGUE TABLE OBSERVATIONS

VARIABLES	(1) Full Sample	(2) Top-Tier	(3) Low-Tier
D_MAV	0.579+	1.367	0.401
	(0.175)	(1.055)	(0.352)
REP_MAV	1.005**	1.178	1.014*
	(0.00152)	(0.128)	(0.00567)
MASH_MAV	1.001	1.038	
	(0.0130)	(0.0669)	
EXP_MAV	1.003	1.004	1.054+
	(0.00375)	(0.00715)	(0.0287)
log_SIZE_AQ	1.374***	1.313*	1.352
	(0.0794)	(0.146)	(0.256)
log_DEALV	1.033	1.127	0.963
	(0.0624)	(0.159)	(0.175)
EXP_AQ	1.154*	1.601***	0.971
	(0.0776)	(0.225)	(0.153)
EXP_TG	0.782	0.503	
	(0.248)	(0.301)	
PERC	0.997	0.998	0.982
	(0.00703)	(0.0144)	(0.0273)
CRB	1.509*	0.942	1.494
	(0.308)	(0.323)	(0.942)
SICSAME	1.113	1.040	1.512
	(0.189)	(0.323)	(0.754)
CASH	1.000	0.999	1.007
	(0.00172)	(0.00322)	(0.00571)
ATT	1.502	1.901	
	(0.665)	(1.760)	
NUMB	0.678	0.163	
	(0.438)	(0.315)	
NUM_AQAV	1.183	1.420*	0.716
	(0.123)	(0.234)	(0.440)
Constant	0.0164**	0.00744	0.0203
	(0.0223)	(0.0229)	(0.0797)
Observations	1,043	302	173
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Pseudo R	0.166	0.247	0.213
Wild Chi-square	154.9***	148.4***	42.10*
Log-likelihood	-537.2	-154.9	-59

Table 21 presents the logistic regressions on switching behavior, where the advisor characteristics are related to the main advisor. Observations where the advisor was not present in the top 500 league tables are removed from the regression analyses. Model 1 represents the full sample. Model 2 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 3 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

TABLE 22: LOGISTIC REGRESSION RESULTS WHERE MAIN ADVISOR CAN BE DETERMINED

VARIABLES	(1) Full sample	(2) Top-Tier	(3) Top-Tier	(4) Low-Tier
D_MAV	0.542	37.81*	2.494	0.0804+
	(0.231)	(67.02)	(2.498)	(0.123)
REP_MAV	1.004**	2.179**	1.390**	1.008
	(0.00136)	(0.629)	(0.158)	(0.00578)
MASH_MAV	0.996	1.234+	1.006	
	(0.0238)	(0.147)	(0.0608)	
EXP_MAV	1.003	1.001	1.011	1.115**
	(0.00659)	(0.0115)	(0.0129)	(0.0429)
log_SIZE_AQ	1.230*	1.691*	1.584**	0.708+
	(0.103)	(0.429)	(0.274)	(0.138)
log_DEALV	1.161+	1.877+	1.289	1.010
	(0.103)	(0.628)	(0.272)	(0.153)
EXP_AQ	1.125+	1.949**	1.229+	0.860
	(0.0717)	(0.431)	(0.145)	(0.162)
EXP_TG	0.857	0.450	0.706	
	(0.273)	(0.247)	(0.535)	
PERC	0.997	1.055+	1.010	1.058
	(0.00795)	(0.0339)	(0.0282)	(0.0512)
CRB	1.464	0.847	0.490	3.955
	(0.425)	(0.437)	(0.330)	(4.665)
SICSAME	1.011	1.553	0.930	1.886
	(0.253)	(1.183)	(0.467)	(1.534)
CASH	0.998	0.994	0.999	1.007
	(0.00264)	(0.00596)	(0.00527)	(0.00836)
ATT	0.909	2.372	3.356	
	(0.578)	(2.453)	(2.753)	
NUM_AQAV	1.036	0.774	0.842	8.866+
	(0.181)	(0.334)	(0.186)	(9.970)
Constant	0.0243**	1.27e-10***	1.57e-05***	6.40e-06+
	(0.0309)	(8.10e-10)	(4.67e-05)	(4.28e-05)
Observations	466	112	121	103
Country FE	Yes	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R	0.183	0.508	0.319	0.338
Wild Chi-square	-	-	35.62**	97.3***
Log-likelihood	-227.7	-38.02	-56.62	-28.31

Table 22 presents the logistic regressions on switching behavior where the main advisor can be determined. The advisor characteristics are related to the main advisor. Model 1 represents the full sample. Model 2 and 3 represent a subsample which only includes deals advised by the top-ranked 25% advisors, where model 3 does not include country fixed effects. Model 4 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

TABLE 23: LOGISTIC REGRESSION RESULTS WITH THEIR CURRENT ADVISOR CHARACTERISTICS

VARIABLES	(1) Controls only	(2) Reputation	(3) Lock-in & reputation	(4) Top-Tier	(5) Low-Tier
D			0.241***	0.496	0.162*
			(0.0973)	(0.436)	(0.130)
REP_AV		1.002*	1.002*	0.645**	1.003+
		(0.000940)	(0.000960)	(0.106)	(0.00182)
MASH_AV	0.990	0.988	0.991	0.832*	
	(0.0137)	(0.0138)	(0.0136)	(0.0595)	
DEAL_AV	1.003	1.006	1.005	1.015+	1.004
	(0.00378)	(0.00401)	(0.00387)	(0.00768)	(0.0220)
log_SIZE_AQ	1.325***	1.348***	1.325***	1.285*	1.228
	(0.0723)	(0.0746)	(0.0739)	(0.139)	(0.177)
log_DEALV	1.011	1.037	1.008	1.156	1.019
	(0.0554)	(0.0585)	(0.0585)	(0.153)	(0.150)
EXP_AQ	1.123+	1.130+	1.192**	1.699***	1.236
	(0.0769)	(0.0758)	(0.0791)	(0.247)	(0.176)
EXP_TG	0.816	0.814	0.752	0.605	
	(0.265)	(0.261)	(0.237)	(0.397)	
PERC	0.995	0.995	0.996	1.000	0.974
	(0.00677)	(0.00674)	(0.00682)	(0.0139)	(0.0209)
CRB	1.439+	1.457+	1.320	1.222	1.018
	(0.279)	(0.283)	(0.257)	(0.423)	(0.592)
SICSAME	1.084	1.096	1.127	1.068	1.735
	(0.182)	(0.184)	(0.191)	(0.328)	(0.706)
CASH	0.999	1.000	1.000	1.000	1.002
	(0.00166)	(0.00167)	(0.00170)	(0.00317)	(0.00475)
ATT	1.643	1.603	1.616	1.843	
	(0.726)	(0.719)	(0.733)	(2.127)	
NUMB	0.632	0.658	0.720	0.147	
	(0.390)	(0.412)	(0.474)	(0.329)	
NUM_AQAV	1.198+	1.184+	1.179	1.432*	0.718
	(0.121)	(0.121)	(0.122)	(0.240)	(0.350)
Constant	0.0389*	0.0222**	0.0327**	4.344	0.633
	(0.0500)	(0.0291)	(0.0431)	(15.54)	(1.846)
Observations	1,097	1,097	1,097	302	222
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R	0.153	0.158	0.174	0.246	0.150
Wild Chi-square	137.2***	147.8***	170.4***	133.1***	30.73
Log-likelihood	-569.7	-566.5	-555.3	-155.1	-86.39

Table 23 presents the logistic regressions on switching behavior where the advisor characteristics are related to the advisor in the current transaction. Model 1 only incorporates control variables. Model 2 only incorporates *REP_AV* as main independent variable. Model 3 incorporates both *REP_AV* and *D* as main independent variables. Model 4 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 5 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

TABLE 24: LOGISTIC REGRESSION RESULTS WHETHER ACQUIRERS RETAIN THEIR MAIN ADVISOR

VARIABLES	(1) Controls only	(2) Reputation	(3) Lock-in & reputation	(4) Top-Tier	(5) Low-Tier
D			4.150***	2.018	6.158*
			(1.675)	(1.775)	(4.944)
REP_AV		0.998*	0.998*	1.551**	0.997+
		(0.000935)	(0.000955)	(0.255)	(0.00181)
MASH_AV	1.010	1.012	1.009	1.202*	
	(0.0140)	(0.0142)	(0.0138)	(0.0860)	
DEAL_AV	0.997	0.994	0.995	0.985+	0.996
	(0.00376)	(0.00397)	(0.00383)	(0.00745)	(0.0218)
log_SIZE_AQ	0.754***	0.742***	0.755***	0.778*	0.814
	(0.0412)	(0.0411)	(0.0421)	(0.0840)	(0.118)
log_DEALV	0.989	0.965	0.992	0.865	0.981
	(0.0542)	(0.0544)	(0.0576)	(0.114)	(0.145)
EXP_AQ	0.891+	0.885+	0.839**	0.588***	0.809
	(0.0610)	(0.0593)	(0.0557)	(0.0854)	(0.115)
EXP_TG	1.225	1.229	1.330	1.652	
	(0.397)	(0.394)	(0.418)	(1.083)	
PERC	1.005	1.005	1.004	1.000	1.026
	(0.00684)	(0.00680)	(0.00687)	(0.0138)	(0.0220)
CRB	0.695+	0.687+	0.758	0.818	0.982
	(0.135)	(0.134)	(0.147)	(0.283)	(0.572)
SICSAME	0.923	0.912	0.887	0.936	0.576
	(0.154)	(0.153)	(0.150)	(0.287)	(0.235)
CASH	1.001	1.000	1.000	1.000	0.998
	(0.00166)	(0.00167)	(0.00170)	(0.00317)	(0.00473)
ATT	0.609	0.624	0.619	0.543	
	(0.269)	(0.280)	(0.281)	(0.626)	
NUMB	1.581	1.520	1.388	6.814	
	(0.976)	(0.953)	(0.914)	(15.28)	
NUM_AQAV	0.835+	0.844+	0.848	0.699*	1.392
	(0.0841)	(0.0864)	(0.0877)	(0.117)	(0.679)
Constant	25.71*	45.11**	30.60**	0.230	1.580
	(33.05)	(59.27)	(40.36)	(0.824)	(4.609)
Observations	1,097	1,097	1,097	302	222
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R	0.153	0.158	0.174	0.246	0.150
Wild Chi-square	137.2***	147.8***	170.4***	133.1***	30.73
Log-likelihood	-569.7	-566.5	-555.3	-155.1	-86.39

Table 24 presents the logistic regressions on whether acquirer retains their main advisor, where the advisor characteristics are related to the advisor in the current transaction. Model 1 only incorporates control variables. Model 2 only incorporates *REP_AV* as main independent variable. Model 3 incorporates both *REP_AV* and *D* as main independent variables. Model 4 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 5 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

TABLE 25: LOGISTIC REGRESSION RESULTS WHETHER ACQUIRERS RETAIN THEIR MAIN ADVISORS

VARIABLES	(1) Controls only	(2) Reputation	(3) Lock-in & reputation	(4) Top-Tier	(5) Low-Tier
D_MAV			1.968*	0.731	3.233+
			(0.570)	(0.564)	(1.948)
REP_MAV		0.998*	0.998*	0.849	0.996*
		(0.000810)	(0.000806)	(0.0920)	(0.00178)
MASH_MAV	1.001	1.003	1.002	0.963	
	(0.0129)	(0.0131)	(0.0130)	(0.0621)	
EXP_MAV	1.000	0.997	0.998	0.996	0.958**
	(0.00350)	(0.00373)	(0.00369)	(0.00709)	(0.0126)
log_SIZE_AQ	0.753***	0.741***	0.749***	0.761*	
	(0.0400)	(0.0400)	(0.0407)	(0.0849)	
log_DEALV	0.991	0.973	0.987	0.887	0.900
	(0.0542)	(0.0545)	(0.0561)	(0.125)	(0.110)
EXP_AQ	0.891+	0.886+	0.863*	0.625***	0.866
	(0.0608)	(0.0593)	(0.0583)	(0.0879)	(0.127)
EXP_TG	1.219	1.230	1.272	1.987	0.226
	(0.396)	(0.397)	(0.403)	(1.187)	(0.298)
PERC	1.005	1.005	1.004	1.002	1.018
	(0.00680)	(0.00678)	(0.00676)	(0.0144)	(0.0180)
CRB	0.694+	0.691+	0.732	1.062	1.096
	(0.135)	(0.135)	(0.144)	(0.365)	(0.591)
SICSAME	0.919	0.906	0.893	0.962	0.538
	(0.153)	(0.151)	(0.150)	(0.299)	(0.225)
CASH	1.001	1.000	1.000	1.001	0.994
	(0.00166)	(0.00167)	(0.00168)	(0.00322)	(0.00419)
ATT	0.618	0.631	0.630	0.526	
	(0.271)	(0.277)	(0.278)	(0.487)	
NUMB	1.598	1.547	1.489	6.134	
	(0.996)	(0.977)	(0.963)	(11.86)	
NUM_AQAV	0.836+	0.842+	0.843+	0.704*	1.237
	(0.0843)	(0.0859)	(0.0863)	(0.116)	(0.499)
Constant	23.54*	37.79**	30.52**	134.4	2.942
	(30.26)	(49.52)	(40.00)	(413.8)	(6.456)
Observations	1,097	1,097	1,097	302	248
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R	0.152	0.156	0.160	0.247	0.161
Wild Chi-square	136.1***	141***	159***	148.4***	44.27*
Log-likelihood	-570	-567.9	-564.9	-154.9	-96.01

Table 25 presents the logistic regressions on whether acquirer retains their main advisor, where the advisor characteristics are related to the main advisor. Model 1 only incorporates control variables. Model 2 only incorporates *REP_MAV* as main independent variable. Model 3 incorporates both *REP_MAV* and *D_MAV* as main independent variables. Model 4 represents a subsample which only includes deals advised by the top-ranked 25% advisors. Model 5 represents a subsample which only includes deals advised by the lowest ranked 25% advisors. Robust standard errors of the coefficient estimates are clustered at firm-level and given in the parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.