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Role of financial advisors on acquisition performance in Europe

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Abstract

Financial advisors play a crucial role in the world of mergers and acquisitions (M&A), due to their extensive knowledge and expertise. However, prior research has not reached a consensus on which financial advisor yields the highest acquisition performance on a deal, whether it is the full-service investment bank or the boutique banks. This study examines the impact of these different financial advisors on acquisition performance in Europe, with a particular emphasis on the impact of deal complexity. The quality of the financial advisor is measured with LSEG's league ranking table and its effect on the cumulative abnormal return, together with a constructed complexity scale. The findings indicate that full-service investment banks generally achieve higher cumulative abnormal return (CAR), but with increased complexity a boutique advisors perform better. Besides, this research distinguishes between investment banks and boutique banks within the league table. These conclusions provide insights for firms in selecting the appropriate advisors to optimize their M&A strategies and outcomes in the dynamic European market.

Keywords: Merger & Acquisitions (M&A), Financial advisor, Investment Bank, Boutique bank, Complexity, League Table

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1 Introduction

According to research by EY, the annual value of merger and acquisition (M&A) deals in 2023 amounted to 34.7 billion euro (O'Brien, 2024). With the size of these transactions and the changes it entails it is of fundamental importance that these transactions are performed well. Besides, M&A deals involve important strategic decisions for both acquirers and targets because they require investments and have several potential risks. These deals are often facilitated by financial advisors¹ in which they provide their specialized knowledge and expertise. The role of financial advisors in these transactions is important to understand for firms, but also for investors and policy makers.

In the current market there is an abundance of financial advisors and the competition to be the financial advisor in a deal is also very strong. Every acquiring company strives to enlist the best advisor who yields the best performance on the deal. The following question arises: which financial advisor yields the highest performance? Logically, this is a broadly researched topic within M&A research, mostly in the United States. Literature states that in the financial advisory market, we mainly see two types of advisors, the large investment banks, and the smaller boutique advisors (Alexandridis et al., 2024; Song et al., 2013). The large investment banks are all the well-known parties like JP Morgan and Goldman Sachs. However, do the larger parties with a better reputation yield a better performance?

Studies state that total wealth gains are larger when either the target or acquirer uses an investment bank as its advisor. Investment banks are able to gain larger synergies and ensure a larger portion of these synergies to the acquirer (Bowers & Miller, 1990; Golubov et al., 2012). Other factors playing a role are: prior acquisition experience of investment banks and a better ability of closing the deal (Bao & Edmans, 2011; Diamond & Maskin, 1981; Mortensen, 1982). On the contrary, studies also state that not the investment banks but the boutique banks yield better acquisition performance. One main argument of these studies is that boutique banks operate

¹ The terms "financial advisors", "investment banks" and "boutique banks" are used interchangeably.

independent and are free of conflict (Loyeung, 2019; McLaughlin, 1992). Thus, in existing literature there is no consensus whether the investment banks or boutique banks yield higher returns in a deal.

Moreover, multiple studies state that complexity is an important aspect of a deal which influences the preference for a type of financial advisor. Those studies all agree on the relationship between the complexity of deals and the need for a financial advisor, when a deal becomes more complex the need or desire for a financial advisor by the management increases substantially (Golubov et al., 2012). Literature argues that both the investment bank and boutique bank financial advisors can reduce information asymmetries in complex deals. Where some studies state that investment banks are hired more often in complex deals (Servaes & Zenner, 1996; Wang et al., 2020) there are also studies which state that boutique banks are hired more often in complex deals (Song et al., 2013). They all point out several factors play a role in determining the complexity of a deal, which are also used in this study to determine the complexity of a deal. Existing literature mentions the following variables: deal value, relative size, whether there are multiple bidders, the form of payment, the deal type, whether the deal was in a period of crisis and whether a deal was in a merger wave (Chuang, 2014; Duchin & Schmidt, 2013a; Loyeung, 2019; Servaes & Zenner, 1996). Nevertheless, the impact of all these complexity factors on the relation between the role of advisors and acquisition performance remains unexplored. While individual complexity variables have been studied, mostly in the United States, this research will construct a complexity scale focused on deals conducted in Europe, as detailed in the methodology section. The focus lies on Europe due to the lack of research on the effect of the complexity variables on European deals. Therefore, this research will answer the following research question:

What is the effect of financial advisors on acquisition performance and how does this effect vary with complexity in Europe?

Additionally, the importance of the effect of the role of financial advisors on acquisition performance extends also to several social aspects. In times of economic uncertainty and boards are unable to navigate through these times, financial advisors can jump in with their knowledge and expertise to steer strategy and make the best strategic and financial decisions. In addition, not only businesses but also policy makers and investors benefit to gain knowledge on the effect on this relationship. Investors can adjust their investment strategy when a potential gain arises if financial advisors drive the performance of an acquisition.

The effect of the role of financial advisors on the acquisition performance is measured by the following methods. Acquisition performance is measured using the cumulative abnormal return of a deal, as specified in the methodology chapter. To measure the quality of the financial advisor's league ranking tables are used to rank the investment banks and boutique banks. Additionally, several complexity variables are incorporated which are also already mentioned above. Moreover, a complexity scale is created which interacts with the financial advisor variable to research the effect of an increased complexity of the deal on the estimated relation.

This paper continues as follows: chapter 2 is an overview of existing literature on the relationship between financial advisors and acquisition performance. Chapter 3 denotes the data collection and the methodology. In chapter 4 there are the results displayed, chapter 5 is the conclusion and discussion, with chapter 6 the references and finally in chapter 7 the appendix.

2 Literature review

In this chapter existing literature will be reviewed regarding the relationship between the type of financial advisor and the acquisition performance. As will be discussed, there is no consensus in literature whether boutique banks and investment banks differ in the quality they deliver in their advisory. First, financial advisors are part of acquisitions transactions due to their comparative advantage. This comparative advantage consists of reducing transactions costs and a reduction of information asymmetries (Bowers & Miller, 1990).

According to Servaes & Zenner (1996) investment banks play a crucial role in reducing transaction costs, they state three reasons. Namely, economies of specialization, scale economies in information acquisition and contracting costs. The contracting costs for example, are diminished due to a decrease in search costs. Financial advisors have a clear market analysis for industries in which they can select the best target for an acquiring firm. Transaction costs are a determinant for the complexity of an acquisition deal, with an increase in complexity the need for financial advice also increases. Complexity determinants are the deal type, the form of payment, the deal volume and many more which will be discussed later. For example, with a hostile takeover, an acquisition with securities or a large transactions tend to be more complex than a friendly small acquisition paid with cash. Additionally, financial advisors can reduce information asymmetries, which are a type of transaction costs. Servaes & Zenner (1996) state that financial advisors have more information on potential buyers and market characteristics than the board of a firm. Financial advisors have gained more information due to prior acquisition experience and industry-specific knowledge. This gives them a comparative advantage in advising both acquiring and target firms.

Clearly, financial investors can play a pivotal role in an acquisition. However, there are different types of financial advisors in the current market. The merger and acquisition market is no longer dominated by investment banks, but boutique banks are also on the rise (Alexandridis et al., 2024; Song et al., 2013). There is no consensus in literature whether investment banks or boutique banks yield a higher return for acquirers.

First, literature state that, assuming market efficiency, the economic quality of a transaction should be reflected in the share prices of both firms involved. This wealth creation at the announcement date gives an estimation of the market's view on the present value of wealth created through the M&A deal (Schierreck et al., 2009). As mentioned, an investment bank performs two roles in a transaction. First, identifying the better merger, which is the merger with the higher expected synergy gains. Second, giving advice and plan strategic actions to acquire the best price for their client (Kale et al., 2003). Literature suggests a hypothesis called "*the superior deal hypothesis*" which states that the prestigious investment banks, are better at identifying merger partners and create greater operational and financial synergies and are better at advising and planning strategic activities (Raghavendra Rau, 2000). This hypothesis predicts that deals advised by an investment banks yield a greater value and therefore wealth gain for the acquiring company (Ismail, 2010). This hypothesis has been empirically supported by the study of Bowers & Miller (1990), they concluded that the combined wealth gain accruing to both acquirers and targets was larger when the bidder of target employed an investment banks financial advisor. This is due to several factors, one is their perceived ability to identify mergers and acquisitions with higher synergies and with that ensuring a larger portion of these synergies accrues to the acquirer (Golubov et al., 2012).

Additionally, financial advisors of investment banks have many acquisition experience, allowing them to leverage a network of potential buyers and sellers and facilitate better matches (Bao & Edmans, 2011; Diamond & Maskin, 1981; Mortensen, 1982). Moreover, financial advisors have an incentive to build a good reputation (Kale et al., 2003). When an advisor performs well in creating value for their clients, their reputation will increase which attracts bigger clients in the future enlarging their market share (Walter et al., 2008). Shapiro (1983) states that "a good reputation if consumers believe its products to be of high quality". Thus, enlarging reputation leads to higher quality and this should be, according to the "*superior deal hypothesis*", lead to higher cumulative abnormal returns. Furthermore, multiple studies suggest that deals with an investment banks have a higher likelihood to close the deal. This however, does not necessarily

translate to a higher deal value (Walter et al., 2008). Moreover, investment banks have an incentive to deliver the best possible deal, as they receive a success fee with a completed deal.

Yet, Raghavendra Rau (2000) state another hypothesis, the “*deal completion hypothesis*”, in which they argue reputation does not impact the outcome, as investment banks are solely motivated to finalize the deal. Due to the strong correlation between advisory fees and deal completion. However, this study does not focus on whether the deal is completed or not, but solely on the performance of the acquisition. This research will control for this by incorporating only deals which are completed. Other studies also provide contradicting hypotheses on why investment banks do not yield a higher acquisition performance (Bao & Edmans, 2011). These will also not be considered; this study focuses on whether the acquisition performance is higher for deals advised by investment banks than deals advised by advisers of boutique banks.

In contrast, other literature states that boutique banks yield higher returns for acquirers and targets (Alexandridis et al., 2024; Loyeung, 2019; McLaughlin, 1992; Raghavendra Rau, 2000). The study of Loyeung (2019) states that boutique advisors operate independently and are free of conflicts. They prioritize the provision of advice rather than other incentives, like investment banks do. Larger financial institutions have a variety of sales, trading, underwriting, research, and lending activities. Literature states that management prefers unbiased advice from professionals whose main product is advice. Investment banks increasingly rely on trading profits and have limited resources for long-term investment banking with their clients (Song et al., 2013). Besides, boutique advisors are industry specialists and gained experience in their respective fields (Ertugrul & Krishnan, 2014). Within boutique advisory there are also two hypotheses considered, namely the “*scale-hypothesis*” and the “*skill-hypothesis*”. The “*scale-hypothesis*” argues that boutique advisors are solely preferred in smaller transactions, and in bigger transactions an investment bank is preferred. Large investment banks prefer to take on larger transactions because they generate higher advisory fees. However, the larger boutique banks, which are also incorporated in the league table ranking, are large enough and able to compete with the full-service investment banks (Song et al. 2013). We control for this “*scale-hypothesis*” by only

incorporating large deals in our sample, to focus mainly on the “skill-hypothesis” of boutique advisors.

However, the “*skill-hypothesis*” states that independent of the size of the transaction the boutique advisors are hired because of their skill (Loyeung, 2019). Song et al. (2013) provide support for the “*skill-hypothesis*” in which they show that deal characteristics affect the firms choice of an advisor. With complex characteristics, like with a hostile deal or with a stock offer boutique advisors are hired more often. Furthermore, it is argued that boutique advisors provide better quality advise due to their independence and knowledge of specified industries (Song et al., 2013). As such, boutique advisors will be preferred, as mentioned, when a deal is complex and when information asymmetries are large (Servaes & Zenner, 1996). However, these arguments were also stated on behalf of the investment bank advisors.

Besides, companies can hire more boutique advisors, but literature has also supported evidence that the boutique advisors yield higher deal outcomes. Song et al. (2013) show that boutique advisors on the acquirer side generate lower premiums paid for the target. On average 8-10% lower premiums paid. This provides evidence that boutique advisors have superior performance in advising M&A deals. Besides, the results of Loyeung (2019) show that on both the acquiror and target side the post-acquisition performance with boutique banks is higher than with large investment banks.

In conclusion, the literature states that financial advisors generally provide additional value to an acquisition deal. However, the empirical results whether investment banks or boutique banks provide superior advice and yield the highest performance remains inconclusive. With all research that has been done on this topic, this paper uses the following hypothesis, because it is commonly assumed, on the financial advisory market, that the bigger investment banks yield higher returns (McCombie, 2022).

Hypothesis H1: Investment banks financial advisors yield significantly higher cumulative abnormal returns than boutique banks financial advisors.

Additionally, another aspect which will be tested in this research is the effect of complexity on this relationship. In the upper section the complexity aspect has been mentioned in both the cases for investment banks and boutique banks. Reviewing the existing literature on the aspect of complexity in this relationship, the effect of complexity on the role of a financial advisor is clear. When a deal becomes more complex, which can be determined by many variables, the need or desire for a financial advisor by the management increases substantially (Golubov et al., 2012). Literature argues that both the investment banks and boutique banks can reduce information asymmetries in complex deals and possess the needed experience and knowledge to best advise the management on the deal (Servaes & Zenner, 1996). For example, Song et al. (2013) states with the “*skill-hypothesis*” that with an increase in complexity more managements will seek the advice of boutique banks. On the contrary, Servaes & Zenner (1996) argue in their research that an investment bank is used more in complex transactions due to the ability to reduce asymmetric information. Wang et al. (2020) reached the same conclusion that with complex transactions investment banks are hired more often.

Many variables are considered in literature to determine whether a transaction is complex. These variables are also incorporated in this research to determine the complexity of a deal. Studies state that deal value is an important complexity variable, the higher the deal value the more complex the transaction (Alexandridis et al., 2024; Loyeung, 2019; Servaes & Zenner, 1996). The relative size of a deal is also an important determinant in the complexity of a deal, the larger the target the more resources they have to resist a takeover bid and are harder to value as they consist of more business units (Loyeung, 2019). Moreover, when there are multiple bidders the deal complexity also increases, because there is higher competition to get the best deal (Servaes & Zenner, 1996). Besides, they state that the form of payment is also important for the complexity of a deal. When the entire deal is paid in cash the complexity is much lower than when a deal is paid in equity or debt. Other studies state that the deal type is also important for the complexity

of a deal, because when a deal is hostile the transactions become way more complex than a friendly takeover (Servaes & Zenner, 1996). Another important factor which influences the complexity of a deal and has several implications is the effect of a financial crisis. Multiple studies have studied this effect, and they state that during a financial crisis the information asymmetries enlarge, and the acquisition transactions become more complex. Studies state that financial intermediaries might be better to guide firms through these economic uncertain times and have the ability to reduce information asymmetries (Chuang, 2014). Literature also states that different industries might also have different complexity levels, they however do not specify which industry leads to higher complexity deals than other industries, thus this will not be incorporated in this study. Moreover, research states that during merger waves the performance of analysts becomes weaker and the acquisition performance decreases during a merger waves. This shows that during merger waves there is a higher complexity of giving the most optimal advice to acquisition deals (Duchin & Schmidt, 2013a).

In conclusion, the role of a financial advisor becomes more important when the complexity of a deal increases. However, literature states that both the investment bank financial advisor and the boutique bank financial advisor both contribute to reducing information asymmetries which are linked to increasing complexity. As mentioned previously, literature states that boutique bankers are often hired in complex transactions, which is also empirically supported (Loyeung, 2019; Song et al., 2013). However, investment bank advisors are also good at tackling these complexity issues as suggested by literature. Yet, this paper uses the following hypothesis because literature states that complex deals is a specialty of the boutique banks.

Hypothesis H2: Boutique banks financial advisors yield significantly higher cumulative abnormal returns than investment banks financial advisors when a deal is more complex.

3 Methodology

3.1 Sample construction

This study investigates the correlation between financial advisors from investment banks and boutique banks concerning acquisition performance. Moreover, the acquisition deal's complexity impact on this relationship is also analysed. Acquisition deals spanning from 2003 to 2023 will be analysed. Only deals involving either the acquiring or target company having a financial advisor will be considered. Specifically, the analysis focusses on deals with listed companies to facilitate the calculation of cumulative abnormal returns. This paper solely focusses on acquisition deals, no other M&A transactions like IPO, buybacks, or other type of transactions. Consistent with previous literature, the sample had several other criteria. Firstly, transactions must be completed (Chahine & Ismail, 2009; Chuang, 2014; Duchin & Schmidt, 2013a), and the transaction deal value must exceed 1 million euro (Golubov et al., 2012; Ismail, 2010). The transaction value must exceed 1 million euro to avoid the "*scale-hypothesis*", which states that boutique financial advisors are solely used for the small transaction values (Song et al., 2013). Given the European focus of this study, the acquirer must be based in Europe. Besides, either the financial advisor of the acquirer or the target must be known. In the retrieved data we always use the first named financial advisor, this is typically the lead advisor of the mentioned party. Furthermore, the deal must entail acquiring 50% or more of the total of shares (Alexandridis et al., 2024; Ertugrul & Krishnan, 2014; Nguyen & Tsai, 2024; Song et al., 2013; Wang et al., 2020). Concluding, the sample of deals must consist of available data for the acquisition performance measure.

The deals mentioned above are retrieved from Orbis M&A database and the corresponding share prices for the estimation window and event window are retrieved from the LSEG Workspace database. Cumulative abnormal returns serve as the metric for measuring the acquisition performance, as literature suggests. The financial advisors are ranked by the means of league ranking tables retrieved from the LSEG workspace, this will be elaborated in upcoming sections.

3.2 Acquisition performance

M&A studies are event studies and literature states that “an event study measures the impact of a specific event on the value of a firm” (MacKinlay, 1997). To conduct an event study, three periods must be specified: an estimation window, event window and post-event window. With M&A transactions the estimation window are one or more days prior to the actual event, which is the acquisition announcement. Studies vary widely on the length of these estimation windows. The period before the event must be long enough to estimate the normal returns of the firms and the period after the event must be long enough to capture the entire effect of the event. The daily stock returns are retrieved from the LSEG Workspace. The estimation period of the normal returns needs to be of a sufficient length, to make sure “rumor’s” do not tamper the estimation of the normal returns of the companies. This paper uses an estimation window of [-252, -20], which is a commonly used proxy for the estimation window in M&A research (Schiereck et al., 2009). The normal daily returns are calculated as follows:

$$1. R_{it} = \frac{(P_t - P_{t-1})}{P_{t-1}}$$

Where,

R_{it} denotes the daily return

P_t denotes the price today

P_{t-1} denotes the price before today

Initially, during the event window, the expected returns must be estimated. Various event windows are documented in literature, but the most common used event window is [-1,+1] (Bowers & Miller, 1990; Golubov et al., 2012; Kale et al., 2003). This time span has been chosen, to review the immediate effect and sentiment of the market towards the completed acquisition. Additionally, to focus solely on the immediate effect of the completed acquisition, an additional regression will be performed to estimate a longer-term effect. The market model is the benchmark to measure the estimated returns:

$$2. ER_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it}$$

Where,

ER_{it} denotes the expected daily return of asset i at time t

α_i denotes the constant return not explained by the market

β_i denotes the stock's sensitivity to the market

R_{mt} denotes the market return

ϵ_{it} denotes the idiosyncratic risk of a stock

All these variables are likewise retrieved from the LSEG Workspace. After calculating the normal returns in the estimation window and the expected returns within the event window, the abnormal returns are calculated. The abnormal returns are calculated as follows:

$$3. AR_{it} = R_{it} - ER_{it}$$

Where,

AR_{it} denotes the abnormal returns of company i at time t .

However, cumulative abnormal returns are more effective in capturing market reactions, as stated by Brown & Warner (1985). The cumulative abnormal returns are calculated as follows:

$$4. CAR_{i,t_1,t_2} = \sum_{t=t_1}^{t_2} AR_{it}$$

A positive cumulative abnormal return states that shareholders updated their beliefs and expect higher returns due to the event, the acquisition. Thus, a high cumulative abnormal return can be seen as good acquisition performance.

3.3 Financial advisors

As stated, this paper researches the distinction between the financial advisors of investment banks and boutique banks. Literature uses various methods to measure the quality of financial advisors, for example Raghavendra Rau (2000) manually created its own tiers on several criteria. Bao & Edmans (2011) used fixed effects to estimate the quality of the financial advisor. Another approach involves the use of league ranking tables, which are retrieved from the LSEG M&A module. These league ranking tables are based on rank value, this rank value is determined by the number of deals performed and the deal value.

All deals in the sample involve a financial advisor and each advisor of the deals assigned a score based on the ranking of the financial advisor in the league table (*FINADV*). In the Appendix, the list of the top 154 ranked financial advisors in Europe is listed. Additionally, all deals in the sample will include an additional variable denoting the acquiror's financial advisor's ranking number. In this variable, the highest ranked financial advisor will be assigned number 1, while the lowest ranked financial advisor is assigned number 154. When the financial advisor is not in the league ranking table, the deal will be ranked with 155. When the relationship indicates a negative relation, deals advised by financial advisors ranked higher, but with lower numerical scores, will lead to higher acquisition performance.

3.4 Complexity

Moreover, as described in the literature overview the relationship between the type of financial advisor and the acquisition performance is heavily influenced by the deal complexity. Literature suggests that as deal complexity increases, the need of a financial advisor increases. However, there is no consensus on whether investment bank financial advisors are better at resolving this complexity within a deal or the boutique bank financial advisors. Literature described multiple variables which need to be considered.

Firstly, deal value (*DEALVALUE*) and the relative size of the deal (*RELATIVESIZE*) are crucial factors as denoted by literature. Additionally, there is also a dummy created for the criterium of

multiple bidders (*MULTIPLEBIDDERS*), which intensifies the complexity. Another complexity variable is the form of payment (*FORMOFPAYMENT*), categorized with a dummy. When the entire deal is paid in cash the complexity is much lower than when a deal is paid in equity or debt. Due to much more complex payment arrangements and different ways of financing the deal like with equity or debt a deal becomes much more complex than solely a cash transaction.

The deal type, whether hostile or not, will also be determined with a dummy (*DEALTYPE*). Hostile deals are much more complex than friendly takeovers. Moreover, there is also the crisis variable, which is a dummy whether the deal was in times of crisis (*CRISIS*). Which is the European Sovereign Debt crisis from 2007 to 2009 or the COVID-19 crisis in 2020. In times of a crisis, it is more difficult to get a good acquisition performance, this increases the complexity of a deal. Another dummy is created for periods of merger waves (*MERGERWAVES*), where literature also suggests that complexity increases. Due to a performance decline in acquisition during a merger wave, the better the adviser the better a deal can be navigated within these waves (Duchin & Schmidt, 2013a). The time periods where merger waves exist is the “sixth wave” which was from 2003 to 2007 (Depamphilis, 2014). Besides, the sixth wave speculations are that there is currently a merger wave, but there has been no literature stating that the current market state is an actual merger wave (*Boom Time*, z.d.). Each of these variables will be individually tested on to evaluate their influence on cumulative abnormal returns in general.

Additionally, all variables will be interacted with the financial advisor variable. Furthermore, a complexity scale (*COMPLEXITYSCALE*) is created to integrate all complexity variables, which will also be interacted with the financial advisor variable. The complexity scale is constructed as follows. The left column in Table 1 describes the separate complexity variables and in the right column the criteria is described. If the deal satisfies a criterium, it is assigned a score of 1 on the complexity scale, with a maximum of 6. This complexity scale variable will also be interacted with the financial advisory variable to estimate how the relation between the financial advisor and cumulative abnormal return changes when complexity increases. The interaction variable will show whether the second hypothesis of this paper is accurate. Additionally, the scale will range from 1 to 7 to avoid the issue of certain deals being multiplied by 0.

Variable	Criteria
Deal value	Deal volume must be larger than average.
Relative size	Relative size of the deal must be larger than average.
Multiple bidders	When the deal consists of multiple bidders
Form of payment	Deal paid differently than in solely cash
Deal type	Deal must be hostile.
Crisis	Deal must be in a period of crisis. 2007 – 2009 (Sovereign Debt crisis) 2020 (COVID-19 crisis)
Merger waves	Deal must be during a merger wave. 2003 - 2007

TABLE 1 – CRITERIA OF THE COMPLEXITY VARIABLES FOR THE COMPLEXITY SCALE

3.5 Control variables

Firstly, a control variable which needs to be considered is the acquisition experience (*ACQUISITIONEXPERIENCE*). The acquisition experience of a financial advisor plays a huge part, as it signifies the expertise and knowledge, as mentioned in literature (Raghavendra Rau, 2000). Besides, another important advisor related control is the fee (*FEES*) the acquiror pays for the services of the financial advisor (McLaughlin, 1992). Additionally, the model also controls for the size of the acquiror (*SIZE*), the acquiror experience (*ACQEXPERIENCE*) and the target experience (*TAREXPERIENCE*). Furthermore, a dummy will be added to control for cross border acquisitions (*CROSSBORDER*), the dummy will be categorized 1 if the acquiror is in a different country than the target.

3.6 Models

First, the relationship between the type of financial advisor and the cumulative abnormal returns controlled for complexity will be tested by using an ordinary least squares regression (OLS). The data will be checked for all assumptions of an OLS regression and will be controlled for any outliers. Influential cases will also be removed from the data and there will also be checked for normal distributed variables. Assuming all assumptions are satisfied after checking the data the basic regression is as follows:

$$5. \quad CAR_{i,t_1,t_2} = \beta_0 + \beta_1 FINADV_i + \beta_2 DEALVALUE_i + \beta_3 RELATIVESIZE_i + \beta_4 MULTIPLEBIDDERS_i + \beta_5 FORMOFPAYMENT_i + \beta_6 DEALTYPE_i + \beta_7 CRISIS_i + \beta_8 MERGERWAVES_i + \beta_9 ACQUISTIONEXPERIENCE_i + \beta_{10} FEES_i + \beta_{11} SIZE_i + \beta_{12} ACQEXPERIENCE_i + \beta_{13} TAREXPERIENCE_i + \beta_{14} CROSSBORDER_i + \varepsilon_{it}$$

Where CAR_{i,t_1,t_2} represents the dependent variable, which states the cumulative abnormal returns of an event window of 3 trading days. β_1 shows if financial advisors have a significant effect on the cumulative abnormal returns of a company. β_2 to β_8 refer to the complexity variables. β_9 to β_{14} are the control variables and ε_{it} functions as an error term. When they data does not satisfy all assumption, the model needs to be adjusted, for example with robust standard errors. But this will be reviewed when the data has been checked.

The second model is the also an OLS regression, but not with all the separate complexity variables, but with the complexity scale variable. The separate complexity variables are then removed from the regression to prevent multicollinearity, because of the correlations between the separate complexity variables and the complexity scale. The correlations of the variables of the merger waves and the crisis with the complexity scale, are relatively high with 0.5 and 0.6. In this model the main independent variable of the financial advisors remains, and the control variables are also incorporated. The second regression of this paper is formulated as follows:

$$6. \text{CAR}_{i,t_1,t_2} = \beta_0 + \beta_1 \text{FINADV}_i + \beta_2 \text{COMPLEXITYSCALE}_i + \beta_3 \text{ACQUISTIONEXPERIENCE}_i + \beta_4 \text{FEES}_i + \beta_5 \text{SIZE}_i + \beta_6 \text{ACQEXPERIENCE}_i + \beta_7 \text{TAREXPERIENCE}_i + \beta_8 \text{CROSSBORDER}_i + \varepsilon_{it}$$

In the third model an interaction variable is added to estimate how complexity changes the relationship between the type of financial advisor and the cumulative abnormal returns. This interaction term multiplies the financial advisor term with the complexity scale term. The rest of the model is the same as the second regression, but this model incorporates the interaction term. The third regression is formulated as follows:

$$7. \text{CAR}_{i,t_1,t_2} = \beta_0 + \beta_1 \text{FINADV}_i + \beta_2 \text{COMPLEXITYSCALE}_i + \beta_3 \text{ACQUISTIONEXPERIENCE}_i + \beta_4 \text{FEES}_i + \beta_5 \text{SIZE}_i + \beta_6 \text{ACQEXPERIENCE}_i + \beta_7 \text{TAREXPERIENCE}_i + \beta_8 \text{CROSSBORDER}_i + \beta_{11} \text{FINADV} * \text{COMPLEXITYSCALE} + \varepsilon_{it}$$

Besides these three models, the league ranking table will be sorted into three tiers, which is in line with the study of Raghavendra Rau (2000). The top 10 of the league ranking table, thus number 1 to 10, will be ranked tier 1 (top-tier). The second tier is the middle-tier, and this tier are financial advisors ranked 11-70 and the third tier is the low-tier and that are financial advisors ranked 71 to 154. Each model will also be performed on these tiers separately, to estimate the effect per tier. This separate effect of the tiers can show an indication how the effect changes between the different tiers and therefore the difference between investment banks and boutique banks. The third model can control for differences between the different tiers and the effect of the financial advisor may vary between the different tiers. Additionally, potentially deals that are not advised by a ranked financial advisor are then eliminated in the models, thus the effect within the league table is also estimated with this third model.

Several robustness checks will be performed to assure the reliability of the above-mentioned models. First, there will be a model to control for potential long-term effects of the type of financial advisor, by taking a larger event window of the cumulative abnormal returns, an event window of 20 days has been used. There will also be controlled for whether the target had a financial advisor which is ranked in the league table. Besides, year and industry dummies will be used to check for time and industry specific factors. Finally, a robustness check will be performed for boutique and full-service banks in the league table ranking.

4 Results

This segment entails the results of the opposed models. The suggested variables fees and relative size are not in the models due to lack of data. Relative size could not be estimated since many of the targets in this sample are not listed. Section 4.1 specifies the descriptive statistics of all variables in the suggested models and section 4.2 analyses the correlation matrix between the variables. In section 4.3 the regression models will be discussed and in 4.4 the robustness checks are presented.

4.1 Descriptive statistics

Table 2 presents the descriptive statistics of the dependent variable, the independent variables, and the control variables for the entire sample spanning from 2003 to 2023. The variables, deal value (*DEALVALUE*) and size of the acquiror (*SIZE*), have been transformed to lognormal variables, for better interpretation (*logDEALVALUE* & *logSIZE*). First, the cumulative abnormal return (*CAR*) is positive with a mean of 0.446, indicating that on average the transactions in this sample positively affect the short-term shareholder returns. The financial advisor (*FINADV*) variable has a mean of approximately 100, due to the high number of financial advisors ranked 155 in the sample. Due to financial advisors who are not ranked get a ranking of 155. Higher values of the financial advisor variable correspond to lower rankings and diminished reputation. Among the complexity dummies, the means of almost all variables are below 0.5 suggesting fewer complex transactions in this sample. The deal type (*DEALTYPE*) of the deals in this sample are mostly friendly, 10 of the 3278 deals has been hostile, thus only 0.3% of the deals has been hostile. Deal type is included in the complexity scale to measure the complexity of the deal. The form of payment (*FORMOFPAYMENT*) has a mean of 0.855 this indicates that most deals in the sample has been paid with a different method than solely cash. There are 476 deals paid with only cash, which is 15% of the total amount of deals. The mean of the multiple bidders (*MULTIPLE BIDDERS*) variable is 0.037, only 121 deals in this sample have had multiple bidders, thus only approximately 3% of all deals in the sample. There are 635 deals in the crisis period performed which results in a mean of 0.194, thus approximately 19%. And there were 581 deals performed in the merger

waves, resulting in a mean merger waves variable of 0.177, thus approximately 18% of the deals. The complexity scale has a mean of 2.426, which states that on the scale the deal has a mean complexity of 2.426.

When looking at the control variables acquisition experience of the acquiror (*ACQEXPERIENCE*) varies from 0 to 44, with a mean of approximately 3 deals. This indicates that acquirers in this sample completed 3 deals between 2003 and 2023, on average before the completed date of a deal. For the experience of targets (*TAREXPERIENCE*) this is lower with a maximum of 3 deals and a mean of 0.541. Targets are often acquired in full which results in lower target experience. The experience in acquisition of financial advisors (*ACQUISITIONEXPERIENCE*) varies from 0 to 160, with a mean of 23. This states that on average a financial advisor has advised 23 deals between 2003 and 2023 before the completed date of the deal in this sample. The logarithm of the size of the acquiror (*logSIZE*) varies between 6.954 and 19.718. The amount of cross border (*CROSSBORDER*) deals and within country deals are somewhat even, 42% of the deals are with a different country of the acquiring and target firm.

TABLE 2: DESCRIPTIVE STATISTICS

Statistic	N	Mean	St. Dev.	Min	Max
DEALVALUE	3,278	601,616.800	2,658,904.000	1,000.000	55,300,000.000
FORMOFFPAYMENT	3,278	0.855	0.352	0	1
CROSSBORDER	3,278	0.422	0.494	0	1
DEALTYPE	3,278	0.003	0.055	0	1
ACQUISITIONEXPERIENCE	3,278	23.034	29.014	0	160
ACQEXPERIENCE	3,278	2.586	4.167	0	44
TAREXPERIENCE	3,278	0.541	0.584	0	3
MULTIPLEBIDDERS	3,278	0.037	0.189	0	1
SIZE	3,278	6,766,407.000	17,770,460.000	1,047	365,819,944
CAR	3,278	0.446	2.760	-6.923	8.116
FINADV	3,278	98.504	65.906	1	155
CRISIS	3,278	0.194	0.395	0	1
MERGERWAVES	3,278	0.177	0.382	0	1
DUMMY TARGETADV	3,278	0.121	0.326	0	1
TARGETADV RANKING	3,278	138.750	45.065	1	155
logSIZE	3,278	13.363	2.421	6.954	19.718
logDEALVALUE	3,278	10.722	2.294	6.908	17.828
DEALVALUEDUMMY	3,278	0.161	0.367	0	1
COMPLEXITYSCALE	3,278	2.426	0.790	1	6

Table 2 represent the descriptive statistics of all variables. It incorporates the number of observations, the mean, the standard deviation, the minimum and maximum value of each observation.

4.2 Correlation Matrix

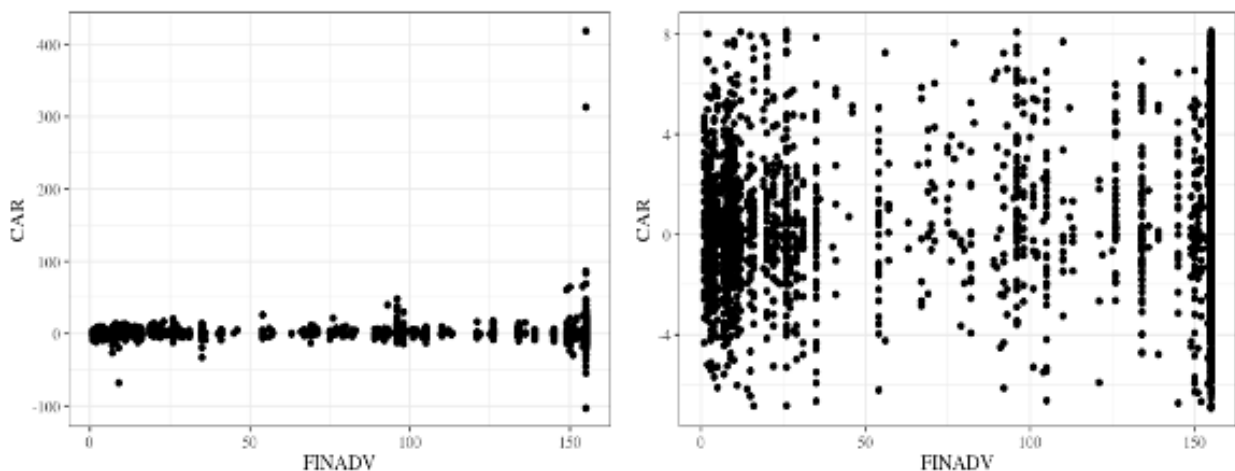
Table 3 in the Appendix shows the correlation matrix, the focus is on correlations above -0.5 and 0.5. Correlations within this range show little to no correlation and pose no issue in our model. Notably, the variables representing the size of the acquiror (*SIZE*) and the deal value (*DEALVALUE*), as well as their logarithmic counterparts (*logSIZE* and *logDEALVALUE*) have a correlation coefficient higher than 0.5, standing at 0.760. This follows logically because acquiror of a bigger size can engage in greater deals which leads to a higher deal value. This elevated coefficient raises concerns of multicollinearity in the model should both factors be included in the model. To address this, the variance inflation factor (VIF) is calculated to test for multicollinearity. In the Appendix the VIF measure for the first estimated model is shown. These scores indicate no

signs of any multicollinearity within the model, and thus, no variables need to be excluded from the model based on their correlations.

4.3 Regression models

As mentioned in the methodology three models will be tested to measure the effect of the ranking of the financial advisor on the cumulative abnormal return. All three models are OLS regressions and to perform these regressions assumptions need to be checked. First, Graph 1 Panel A shows a positive linear relation between the ranking of the financial advisor and the cumulative abnormal return. Indicating that the lower on the ranking list, a higher value of the financial advisor variable, results in higher cumulative abnormal return. However, Panel A also shows outliers which need to be controlled for. In Panel B of Graph 1 the same variables are outlined but without the outliers. The data without the outliers is the data that is used in the regressions.

GRAPH 1: SCATTERPLOT OF THE RANKING OF FINANCIAL ADVISORS AND CUMULATIVE ABNORMAL RETURN



Graph 1 Panel A shows a scatterplot of the ranking of the financial advisors on the x-axis and the cumulative abnormal return on the y-axis of the initial dataset including outliers. Panel B shows the same variables but without the outliers which will be used for all models.

Besides, in the Appendix several tests have been performed to check if the models do not entail any heteroskedasticity or autocorrelation. The Durbin Watson (DW) test is performed to test whether the models encompass any autocorrelation. The three DW statistics all are approximately 2, which indicates the three models have no autocorrelation. The Breusch Godfrey test is used to test whether the three models entail any heteroskedasticity, all three p-values are highly significant. Thus, all three models show sign of heteroskedasticity. Because, of the heteroskedasticity all models have been controlled with robust standard errors. The Appendix also encompasses a graph of the residuals of the first model. The residuals follow a normal distribution which states that there are no problems for the statistical tests.

In the Appendix Table 13 shows the separate relation of the ranking of the financial advisor in the full sample and the separate tiers to the cumulative abnormal return. The full sample indicates that the relation of the ranking of the financial advisor is positive, suggesting the lower the ranking the higher the cumulative abnormal return ($\beta = 0.001$). The top and low tiers show a negative relation in which the low tier is significant ($\beta = -0.014, p < 0.05$). Suggesting that the higher the ranking the higher the cumulative abnormal return.

4.3.1 Model 1: the effect of the ranking of financial advisors and the separate complexity variables on the cumulative abnormal returns

The first model is displayed in Table 3. The left column shows the first model of the full sample. In the Appendix Graph 3 displays the histogram of the financial advisor variable, this indicates that there are many deals where the financial advisors are not in the league table ranking. These deals advised by non-ranked financial advisor are not considered in the last three models, where the three tiers are measured separately. The methodology specifies these separated tiers.

Table 3 indicates that the full sample has a very small negative insignificant relation between the ranking of financial advisor (*FINADV*) and the cumulative abnormal return ($\beta = -0.001$). This insignificant negative relation states that when the value of ranking increases the cumulative

abnormal return decreases, and thus lower ranked financial advisors perform worse. However, this effect is insignificant. In the top 10 of the financial advisors there is a positive insignificant relation with the ranking of the financial advisor and the cumulative abnormal return ($\beta = 0.001$). This suggests that in the top 10 of the league ranking, the financial advisors ranked lower should perform better than the highest ranked financial advisors, but this effect is also insignificant. However, for the middle and low ranked the effects switches around and becomes negative. Thus, this result indicates for the middle and low ranked financial advisors a higher ranked financial advisor, thus with a lower value of the variable, performs better than a lower ranked financial advisor. However, the middle tier is insignificant on the suggested effect. The low tier shows a significant negative effect ($\beta = -0.014, p < 0.05$) indicating the higher ranked financial advisor performs better than a low ranked financial advisor.

Reviewing the complexity variables the logarithm of the deal value (*logDEALVALUE*) shows for the full sample a small negative insignificant relation with cumulative abnormal returns ($\beta = -0.007$). Indicating that when the deal value increases the cumulative abnormal return decreases, however this effect is insignificant. In the top tier of the financial advisors the effect becomes positive, suggesting that with a smaller deal value the cumulative abnormal return decrease. In the middle and low tier, the relation becomes negative again, however all tiers are insignificant.

The form of payment (*FORMOFPAYMENT*) shows for the full sample a negative insignificant relation with the cumulative abnormal return, stating that when the deal is paid with any other payment method than cash the cumulative abnormal return decreases ($\beta = -0.083$). This effect is the same for the top and middle tier however in both models the effect is insignificant. In the low tier, the effect turns around and becomes positive, however this effect is also insignificant.

The deal type (*DEALTYPE*) has in the full sample and in all tiers a negative relation with the cumulative abnormal return. In the full sample and in the low tier this relation is significant and suggests that hostile deals have a negative relation with the cumulative abnormal return (*full*: $\beta = -0.995, p < 0.05$, *low tier*: $\beta = -1.966, p < 0.01$).

If the deal had multiple bidders (*MULTIPLBIDDERS*), the effect is positive and insignificant for the full sample ($\beta = 0.010$). For the top-tier financial advisors this effect is even stronger but remains insignificant ($\beta = 0.176$), indicating that when a deal had multiple bidders the top-tier financial advisors yield significant higher cumulative abnormal returns, however this relation is also insignificant. For the middle and low-tier financial advisors this effect is negative, but insignificant.

When a deal is completed in a crisis the effect on the cumulative abnormal return is negative for the full sample and the top tier, with a significant effect in the top-tier ($\beta = -0.464, p < 0.05$). For the middle and low tier, the effect of a completion within a crisis is positive on the cumulative abnormal returns, but these effects are insignificant.

When a deal is completed in a merger wave the full sample shows a negative significant effect, indicating that when a deal is completed in a merger wave the cumulative abnormal return is lower ($\beta = -0.232, p < 0.1$). In the top tier and the low tier this effect is also negative, however insignificant. On the contrary, the middle tier shows a positive effect with the cumulative abnormal return, but this relation is insignificant.

Analysing the control variables, cross border deals have in the full sample and in the middle and low tier a negative relation with the cumulative abnormal return, indicating that when a deal is completed cross border the cumulative abnormal return decreases. The low tier shows a significant negative effect with the cumulative abnormal return $\beta = -0.721, p < 0.05$. However, in the top tier this relation is positive. Acquisition experience of the financial advisor has a very small negative relation except for the top tier where the relation is positive. Only the low tier shows a significant negative effect with the cumulative abnormal return $\beta = -0.011, p < 0.05$. The acquirors experience relation with cumulative abnormal return is positive in the full sample and in all tiers. Suggesting that when the experience of the acquiror is higher the full sample indicates that the cumulative abnormal return is lower. However, these results are all insignificant. The target experience's relation with the cumulative abnormal return is in the full

sample and in the middle tier negative, and in the top and low tier positive. However, all results are insignificant. The logarithm of the size shows in the full sample, the top tier, and the middle tier negative results. In the full sample and the top tier this relation is significant. Indicating that with an increase in size of the acquiror the cumulative abnormal return decreases. Only the low tier shows a positive result, however this relation is insignificant.

TABLE 3: MODEL 1

	CAR			
	(Full)	(Top)	(Middle)	(Low)
FINADV	-0.001 (0.001)	0.001 (0.028)	-0.003 (0.010)	-0.014** (0.006)
logDEALVALUE	-0.007 (0.034)	0.098 (0.061)	-0.058 (0.082)	-0.018 (0.115)
FORMOFPAYMENT	-0.083 (0.130)	-0.072 (0.228)	-0.444 (0.368)	0.407 (0.400)
CROSSBORDER	-0.056 (0.104)	0.293 (0.199)	-0.017 (0.266)	-0.721** (0.317)
DEALTYPE	-0.995** (0.474)	-0.493 (1.001)	-0.128 (0.881)	-1.966*** (0.510)
ACQUISITIONEXPERIENCE	-0.002 (0.002)	0.003 (0.003)	-0.003 (0.003)	-0.011** (0.004)
ACQEXPERIENCE	0.013 (0.013)	0.035 (0.038)	0.003 (0.043)	0.042 (0.026)
TAREXPERIENCE	-0.059 (0.094)	0.087 (0.168)	-0.286 (0.233)	0.055 (0.250)
MULTIPLEBIDDERS	0.010 (0.268)	0.176 (0.454)	-0.220 (0.794)	-0.466 (0.700)
logSIZE	-0.081** (0.032)	-0.159** (0.073)	-0.040 (0.078)	0.135 (0.097)
CRISIS	-0.004 (0.129)	-0.464** (0.229)	0.399 (0.399)	0.118 (0.404)
MERGERWAVES	-0.232* (0.130)	-0.227 (0.228)	0.113 (0.358)	-0.295 (0.488)
Constant	1.859*** (0.413)	1.218 (1.093)	2.302** (1.102)	1.022 (1.419)
N	3278	713	496	496
R ²	0.007	0.019	0.016	0.016
Adjusted R ²	0.004	0.002	-0.009	-0.009
Residual Std. error	2.755	2.405	2.736	2.736
F	2.025**	1.133	0.634	0.634

Table 3 presents the OLS regression on CAR (-1,+1). The first column is the full sample, the other three columns are the different tiers specified in the methodology. Robust standard errors are incorporated in the brackets. *** p<0.01, p **p<0.05, * p<0.1.

4.3.2 Model 2: the effect of the financial advisor ranking and the complexity scale on the cumulative abnormal returns.

In Table 4 the results of the second model are presented, now the complexity variables are excluded, and the complexity scale is added. First, the effect of the ranking of the financial advisors does not differ much with the first model. All coefficients remain the same, except for the middle tier where the relation becomes 0.001 smaller. The complexity scale variable shows an insignificant negative relation in the full sample, the top tier, and the middle tier financial advisors. This indicates that when the complexity increases of a deal the cumulative abnormal return decreases. Which is in line with the hypothesis. However, the complexity scale shows in the low tier a positive relation, indicating that deals advised by low-tier financial advisors the more complex deals yield higher cumulative abnormal return ($\beta = 0.138$). Besides, the results of the other variables, the control variables, show no significantly different results than the results displayed in the first model.

TABLE 4: MODEL 2

	CAR			
	(Full)	(Top)	(Middle)	(Low)
FINADV	-0.001 (0.001)	-0.004 (0.028)	-0.002 (0.009)	-0.014** (0.006)
COMPLEXITYSCALE	-0.076 (0.061)	-0.121 (0.100)	-0.015 (0.194)	0.138 (0.230)
ACQUISITIONEXPERIENCE	-0.002 (0.002)	0.003 (0.003)	-0.005 (0.004)	-0.010** (0.004)
ACQEXPERIENCE	0.014 (0.012)	0.020 (0.038)	0.009 (0.042)	0.041 (0.031)
TAREXPERIENCE	-0.090 (0.089)	0.016 (0.165)	-0.222 (0.223)	-0.010 (0.242)
CROSSBORDER	-0.053 (0.103)	0.275 (0.199)	-0.014 (0.259)	-0.711** (0.308)
logSIZE	-0.081*** (0.025)	-0.082 (0.066)	-0.067 (0.064)	0.124 (0.077)
Constant	1.872*** (0.389)	1.550 (1.033)	1.723* (1.006)	0.972 (1.361)
N	3278	713	496	496
R2	0.006	0.008	0.009	0.044
Adjusted R2	0.004	-0.001	-0.006	0.029
Residual Std. error	2.754	2.409	2.731	2.863
F	3.043***	0.855	0.613	2.985***

Table 4 presents the OLS regression on CAR (-1,+1). The first column is the full sample, the other three columns are the different tiers specified in the methodology. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1.

4.3.3 Model 3: the effect of the financial advisor ranking, the complexity scale, and the interaction term on the cumulative abnormal returns.

The outcomes of the third model are outlined in Table 5, this model incorporates an interaction term of the complexity scale and the financial advisor. The initial variables, financial advisor and complexity scale are in this model centered and therefore show the relation with the cumulative abnormal return when the other variable is at its mean. The centered ranking of the financial advisor has not changed much in comparison the model 1 and model 2. The centered financial advisor variable shows that with an average complexity of a deal the effect does not change from model 1 and 2 and that the full sample and all tiers show a negative effect with the cumulative abnormal return. Within the low tier a significant negative relation, indicating that an average complex deal higher ranked advisors yield higher cumulative abnormal return. The centered complexity scale showed also no different results in the full sample and in the middle and low tier. However, in the top tier the centered complexity scale shows a strong significant positive relation with the cumulative abnormal return. Indicating that when the complexity of a deal increases of deals advised by top advisors the cumulative abnormal return increases significantly $\beta = 5.978, p < 0.05$.

The interaction term shows in the full sample a very small positive relation with the cumulative abnormal return ($\beta = 0.0001$). Stating that when the complexity increases the effect of the ranking of the financial advisor becomes stronger on the cumulative abnormal return. Thus, financial advisors who are ranked lower yield higher cumulative abnormal returns when complexity is higher. This is the same for the top tier, and in the top tier this result is significant ($\beta = 0.066, p < 0.05$). This is in line with the hypothesis that higher ranked advisors yield higher cumulative abnormal return.

In the middle and low tier, the result switches and becomes negative. Indicating that when complexity is high the higher the financial advisor is ranked the lower the cumulative abnormal

return, indicating that higher ranked financial advisors perform worse in complex deals. These results however are insignificant.

TABLE 5: MODEL 3

	CAR			
	(Full)	(Top)	(Middle)	(Low)
FINADV_centered	-0.001 (0.001)	-0.030 (0.029)	-0.004 (0.010)	-0.018*** (0.006)
COMPLEXITYSCALE_centered	-0.076 (0.062)	5.978** (2.623)	-0.692 (1.190)	0.428 (0.308)
ACQUISITIONEXPERIENCE	-0.002 (0.002)	0.003 (0.003)	-0.005 (0.004)	-0.010** (0.004)
ACQEXPERIENCE	0.014 (0.012)	0.018 (0.038)	0.009 (0.042)	0.043 (0.029)
TAREXPERIENCE	-0.090 (0.090)	0.015 (0.166)	-0.234 (0.227)	0.002 (0.238)
CROSSBORDER	-0.053 (0.103)	0.262 (0.199)	-0.018 (0.259)	-0.682** (0.309)
logSIZE	-0.081*** (0.025)	-0.083 (0.066)	-0.066 (0.064)	0.117 (0.077)
FINADV_centered: COMPLEXITYSCALE_centered	0.0001 (0.001)	0.066** (0.028)	-0.009 (0.016)	-0.015 (0.010)
Constant	1.603*** (0.339)	-1.486 (2.954)	1.332 (1.080)	0.049 (0.969)
N	3278	713	496	496
R2	0.006	0.015	0.010	0.050
Adjusted R2	0.004	0.004	-0.007	0.033
Residual Std. error	2.754	2.403	2.733	2.857
F	2.663***	1.315	0.598	2.982***

Table 5 presents the OLS regression on CAR (-1,+1). The first column is the full sample, the other three columns are the different tiers specified in the methodology. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

4.4 Robustness checks

4.4.1 Ranked target advisor.

Bowers and Millers (1990) stated in their research that when targets are advised by a top ranked financial adviser the acquiring company yields lower cumulative abnormal return. To control for this the deals in the sample have been separated by deals where the target is advised by an advisor in the league table and when the target advisor is not. The results of the full sample of both the deals advised with a target advisor and not are presented in the appendix Table 14. The data has not been divided into tiers due to a lack of data of ranked target advisors in the used sample.

The first model shows that when the target is advised by an advisor in the league ranking table the ranking of the financial advisor of the acquiror has a positive effect on the cumulative abnormal return. Indicating that when the ranking of the financial advisor increases the lower the cumulative abnormal return when there is a ranked target advisor. However, this result is insignificant. However, without a target advisor the relation of the ranking of the acquirors financial advisor with the cumulative abnormal return switches and becomes negative. But both these results are insignificant, and the sign of the results are therefore only indicators. Yet, the sign of the relation between the ranking of the financial advisor of the acquiror and the cumulative return separated by the ranking of the target advisor remains the same across all three models.

In the second model the effect of the complexity variables, logarithm of the deal value, form of payment, deal type, multiple bidders and logarithm of the size all switch around when the deal has no ranked target advisor. However, the complexity scale in the second model has the same sign for both with and without a ranked target advisor.

The third model shows that the interaction term switches signs for the deals with a ranked financial advisor and without a ranked financial advisor. With a ranked financial advisor, the interaction term is negative, indicating that when the complexity increases the effect of the

financial advisor of the acquiror weakens towards the cumulative abnormal return, indicating that higher ranked financial advisors have higher cumulative abnormal return when the complexity increases. However, no conclusions can be drawn because the results are insignificant. This effect switches around when there is no ranked target advisor.

4.4.2 Long term cumulative abnormal return

In the appendix in Table 15, Table 16 and Table 17 the same three models have been regressed, also divided in tiers but for a longer event window of the cumulative abnormal returns. As literature stated the effect of the advice of a financial advisor could be visible later. The long term cumulative abnormal return is calculated with an event window of 20 days.

The first model, Table 15, shows no significant results for the effect of the ranking of the financial advisor on the long term cumulative abnormal return. In the full sample and top tier there is a small positive effect of the ranking of financial advisors on the long term cumulative abnormal return. In the middle and low tier this switches around to a negative effect. In the first model the complexity variables have all the same sign of the effect, except for the deal type. However, this relation is insignificant, where in the original first model this result was significant.

The second model, Table 16, shows the same results of the effect for the ranking of the financial advisors and the long term cumulative abnormal return. However, the complexity scale shows in the full sample and in all tiers a negative relation with the cumulative abnormal return. In the full sample and in the top tier this relation is significant. Indicating that when a deal is more complex the long term cumulative abnormal return decreases.

The third model, Table 17, incorporates the interaction variable. In the full sample the interaction variable is slightly positive and in all tiers the interaction variable is negative. The full sample indicates that when complexity increases the effect of the ranking of the financial advisor becomes stronger, suggesting the higher ranked the lower the long term cumulative abnormal return when complexity increases. However, this effect is in all tiers the other way around, but all results are insignificant.

4.4.3 Year and industry dummies

In the appendix Table 18 shows the three original models but included with year dummies. The reference category is year 2003, which is the start of the sample. The differences in years in the sample do not show any signs of any unobserved time factors that could potentially bias the results. There are no major changes in the data when controlled for year specific factors. This shows that the initial relation captures are not biased by any time-specific factors.

Moreover, in the appendix Table 19 shows the three original models but included with industry dummies. The reference category is the manufacturing industry, because as Table 12 in the appendix shows this is the industry where most deals are completed. In both three models the effects don't change significantly. This robustness check shows that there are no industry specific controls that need to be accounted for. Therefore, the heterogeneity between industries does not influence the relation between complexity, the ranking of the financial advisor and the cumulative abnormal returns.

4.4.4 Boutique and full-service banks

As literature states we need to distinguish the boutique banks and the full-service banks. However, in the league table ranking there are also boutique banks in the top 10. For example, Lazard is ranked 8 in league ranking table while this is still a boutique bank. To control for this, separate datasets have been created of deals advised by boutique banks in the league ranking table and of full-service banks. To determine which bank in the ranking is a full-service bank and which bank is a boutique bank, all ranked financial advisors have been reviewed. By determining based on their websites and services they are offering at their website. The results are displayed in the appendix in Table 20, Table 21, Table 22 and Table 23, all sorted by tier.

In the full sample the boutique and full-service banks have the same relation of the ranking of the financial advisor on the cumulative abnormal return in all three models. However, most

remarkably is that boutique advisors have a positive interaction variable where the full-service bank have a negative interaction variable. This indicates that for boutique banks an increase in complexity yields a weaker effect of the ranking of the financial advisor on the cumulative abnormal return. Or differently stated it indicates that boutique financial advisors ranked higher yield higher cumulative abnormal return when a deal is complex. For the full service this effect is the other way around.

In the top tier the effect of the ranking of the financial advisor with boutique banks is positive in the first and second model, where the full-service banks show a negative effect of the ranking of the financial advisor on the cumulative abnormal return. However, these results are insignificant. Remarkable is the high and significant coefficient for the centered complexity scale in the third model for the boutique banks, indicating that when the ranking of the financial advisor in the top tier is at its mean the higher the complexity the higher the cumulative abnormal return. For the boutique banks as the full service banks the interaction term is positive, for the boutique banks this effect is significant ($\beta = 0.113, p < 0.05$).

In the middle tier the effect of the ranking of the financial advisor is the same as in the top tier. The boutique bank show in the first and second model a negative relation with the cumulative abnormal return, and the full-service banks show a positive relation with the cumulative abnormal return. However, in the middle tier, the complexity scale is in the boutique bank sample negative and in the full-service sample positive, however both results are insignificant. However, in the third model the boutique bank sample and full-service bank sample are both negative. Besides, in the middle tier indicates in the third model that the interaction term is negative for both the boutique banks and full-service banks. These results are again insignificant.

In the low tier the effect of the ranking of financial advisors is the same for boutique and full-service banks and all show a negative relation, the second model in the boutique bank sample is significant $\beta = -0.018, p < 0.05$. In the boutique bank sample, the complexity scale variable is positive and in the full-service bank the complexity variable is negative, however both are

insignificant. In the third model the boutique bank sample the centered ranking of the financial advisor has a negative significant on the cumulative abnormal return $\beta = -0.021, p < 0.05$. The full-service bank sample also had a negative effect but was insignificant. In the low tier the interaction variable for both the boutique banks and full-service banks shows a negative effect.

5 Discussion & conclusion

Given the substantial annual value of merger and acquisition deals, the executions are tremendously important. Financial advisors play a key role in achieving the highest return on these deals, leveraging their knowledge and expertise to boost returns. Despite this, there is no consensus which type of financial advisor yields the highest cumulative abnormal return. This paper focusses on the differences of investment banks and financial advisors and their effects on the cumulative abnormal return. Additionally, it investigates how deal complexity influences the relation between financial advisor and cumulative abnormal return.

To address the research question two hypotheses were developed. First, whether investment banks or boutique banks generate higher cumulative abnormal returns, and second whether investment banks or boutique banks yield higher cumulative abnormal returns when the complexity of deal increases. This chapter discusses the results and reviews the hypotheses. Furthermore, the findings are compared to those of prior research results. The chapter concludes with a brief conclusion of the research and elaborates on the contributions, limitations, and recommendations for further research.

5.1 Discussion and interpretation of the results

The first model shows that the ranking of the financial advisor has a negative relation with the cumulative abnormal return. Indicating that the higher the financial advisor is ranked the higher the cumulative abnormal return on the deal. However, this is only an indicator because the results are not significant. In the lowest tier this result is significant, thus suggesting that in the lowest ranked financial advisor it is better to hire a higher ranked financial advisor. This result is than in line with the first suggested hypothesis of this research, which states that investment banks are

better at acquiring higher cumulative abnormal returns. Looking at the separate complexity variables, most variables have the expected sign. When deal value increases the full sample, middle and low tier show a negative sign. Suggesting that when deal value increases the cumulative abnormal return decreases, however the top tier shows a positive sign. Indicating that top tier advisors are yield higher returns when the deal value is larger. This is again in line with the suggested hypothesis. The form of payment and deal type shows its expected sign, that with a complexity increase the cumulative abnormal return increases. The full sample and the top tier of the multiple bidders variable shows that when multiple bidders were present in the deal process the cumulative abnormal return is higher. However, this is not the case for deals advised by the middle and low tier. On the contrary, deals completed in a period of a crisis the middle and low tier yield higher cumulative abnormal return, where the full sample and the top tier show a negative sign. This indicates that the middle and low tier advisors are better in advising deals in terms of crisis. When a deal is in a merger wave only the middle tier financial advisors yield higher cumulative abnormal return. However, these are all indicators because most of the results are insignificant.

In the second model the complexity variable shows a negative relation with the cumulative abnormal return in the full sample, in the top tier and in the middle tier. However, in the low tier the complexity variable shows a positive relation, indicating that deals advised by low tier advisers where the complexity is higher the cumulative abnormal return is higher. This is in line with the second hypothesis, stating that boutique banks are yield higher cumulative abnormal return when the complexity increases. However, these results are all insignificant and these relation signs can only be reviewed as indicators.

The third model shows for the ranking of the financial advisor when centered, where the deal complexity is at its mean a negative relation with the cumulative abnormal return. Indicating that with a mean complexity higher ranked financial advisors yield higher cumulative abnormal return, with a significant result in the low tier. When the financial advisor ranking is at its mean the top and low tier show a positive relation of complexity with the cumulative abnormal return,

indicating that in the top and low tier when deal complexity increases the cumulative abnormal return increases. Indicating that both investment banks and boutique banks yield higher returns when complexity increases. Looking at the interaction term the full sample and top tier show a positive sign that when complexity increases the effect of the financial advisors increases and the top ranked advisors yield lower cumulative abnormal returns. The middle and low tier show a negative result indicating that lower ranked financial advisors yield higher cumulative abnormal returns when deals are complex. Which is in line with the suggested hypothesis, that boutique banks yield higher cumulative abnormal returns when complexity increases. However the effect in the middle and low tier is insignificant, but the effect for the top tier is significant.

One of the limitations of the league ranking tables is that there are also boutique banks in the top tier of the ranking. There has been a robustness check where boutique and full-service banks are separated. Remarkably is that in the top tier the boutique banks show in all models a positive sign, indicating that lower ranked boutique advisors yield higher cumulative abnormal returns. Where full-service banks show a negative sign indicating that higher ranked full-service banks yield higher returns. In the third model, when the ranking of the financial advisor is at its mean, the complexity scale shows a big positive significant result. Indicating that in the top tier boutique banks yield very high cumulative abnormal return when complexity increases. Full-service banks also show a positive sign, however insignificant and much smaller than for the boutique banks. The interaction term is for both boutique banks and full-service banks positive, but the boutique banks have a bigger coefficient and is significant. Indicating that when complexity increases the lower ranked boutique advisors yield better cumulative abnormal return, which is in line with the hypothesis.

5.2 Comparison to prior research

First, as highlighted multiple times in this research previous research had not consensus on the relation of financial advisors and cumulative abnormal returns and deal complexity. The results of this paper can be both in line with previous research as in contradiction to previous literature. The first hypothesis of this paper states that investment banks yield higher cumulative abnormal

return than boutique advisors. This is in line with multiple different research. For example, Kale et al. (2003) did find similar results that bidders with a more prestigious investment bank as their advisor associated with greater wealth creation. Besides, Bowers & Miller (1990) also find evidence that combined wealth gain accruing to both acquirers and targets was larger when the bidder of target employed an investment banks financial advisor. However, it contradicts with research like Raghavendra Rau (2000) they showed that deals involving top tier advisors the cumulative abnormal returns are not higher than that of less prestigious advisers. However, that study focusses on mergers and tender offers, while this study focusses on acquisitions. Additionally, the study had a timespan of 1980 to 1990 and this study has a much more recent time span. Adding up, they only reviewed the 25 biggest financial advisor, and this study focusses on 154 different financial advisors. And it also contradicts McLaughlin (1992) because they also stated that announcement returns were significantly lower for top tier advisors than for lower tier advisors. McLaughlin (1992) has also a much older dataset which also focusses on tender offers and had a very small sample of deals to estimate the relation. This could be an explanation of the discrepancy in the results.

Looking at the second hypothesis, where deal complexity plays a pivotal role, the hypothesis stated that boutique banks yield higher cumulative abnormal returns when a deal becomes more complex. The findings in this research are in line with this hypothesis and are besides in line with previous research (Loyeung, 2019; Servaes & Zenner, 1996). Loyeung (2019) findings state that boutique financial advisors are preferred when a deal is considered complex and when information asymmetry is high. The use of boutique advisors impacts the takeover outcomes positively. However, this study was performed in Australia and this study in Europe. The results are also in line with the study of Song et al. (2013), however they estimated the relation with a two-step analysis, which is not aligned with the research method in this study. On the contrary, Bao & Edmans (2011) find an investment bank fixed effect that investment banks yield a significantly higher result. However, this result used a very different method of estimating the relation between the advisor and the cumulative abnormal return. The bank fixed effect is a much broader research method and does not specifically focus on the relation between the financial

advisor and the cumulative abnormal return. This could influence the differences in results and conclusion.

5.3 Conclusion, contribution, limitations, and recommendations for further research

Concluding, both hypotheses are supported in this papers' findings. First, financial advisors who are higher ranked on the league table ranking yield higher cumulative abnormal return. Second, when a deal becomes more complex financial advisors ranked lower yield higher cumulative abnormal returns. In order of answering the research question of this paper: "*What is the effect of financial advisors on acquisition performance and how does this effect vary with complexity in Europe?*" financial advisors ranked higher yield a better acquisition performance but that effect changes when a deal becomes more complex. This research contributes to existing literature because it shows several different ways the relation of the effect of financial advisors on acquisition performance. In the robustness checks it is visible that the effect of the relation changes much, for example with a long term cumulative abnormal return, with complexity scale and an interaction term, whether the target has a ranked financial advisor. All these changes in the analysis influences the effect of the ranking of the financial advisor on the cumulative abnormal return.

This research also has several limitations. First is the use of the league table ranking as a measure for the quality of a financial advisor and distinguishing the investment full-service banks and the boutique banks. Prior research all used very different metrics to measure the quality of the financial advisor or to estimate whether an advisor is an investment full-service banks or a boutique bank. This imbalance could be the driver of the lack of consensus in literature. Additionally, another limitation of this research is that only the first named financial advisor is used. When retrieving the data from the Orbis M&A database multiple financial advisors were mentioned in the deal. For simplicity this research used only the first listed financial advisor. Results may vary substantially when all financial advisors were used in the analysis. Furthermore, in some of the models where the data was separated in the different tiers the number of deals for the analysis were relatively low.

Further research should focus on the different metrics that are being used to measure the quality for the financial advisor. A metric solely based on market value is not the best indicator to estimate the difference between boutique and full-service banks. Besides, research has used multiple different methods to estimate the relation between the ranking of the financial advisors and the acquisition performance. Another suggestion for further research is to take all financial advisors into account and not only the first named advisor, perhaps this could lead to very different results. In which perhaps also the number of different advisors might play a role or when an acquiring company has both the input of a full-service investment bank and a boutique bank. Furthermore, this study has solely focussed on acquisitions, the effect might be different for other kind of deals, like mergers, tender-offers or carve-outs etc.

6 References

- Alexandridis, G., Antypas, N., & Lee, V. Y. (2024). Do boutique investment banks have the Midas touch? Evidence from M&As. *European Financial Management*, 30(1), 634-672. <https://doi.org/10.1111/eufm.12425>
- Bao, J., & Edmans, A. (2011). Do Investment Banks Matter for M&A Returns? *Review of Financial Studies*, 24(7), 2286-2315. <https://doi.org/10.1093/rfs/hhr014>
- Boom time: Riding the seventh great 'M&A wave'*. (z.d.). Financier Worldwide. Geraadpleegd 15 maart 2024, van <https://www.financierworldwide.com/boom-time-riding-the-seventh-great-ma-wave>
- Bowers, H. M., & Miller, R. E. (1990). Choice of Investment Banker and Shareholders' Wealth of Firms Involved in Acquisitions. *Financial Management*, 19(4), 34-44. <https://doi.org/10.2307/3665608>
- Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1), 3-31. [https://doi.org/10.1016/0304-405X\(85\)90042-X](https://doi.org/10.1016/0304-405X(85)90042-X)
- Chahine, S., & Ismail, A. (2009). Premium, merger fees and the choice of investment banks: A simultaneous analysis. *The Quarterly Review of Economics and Finance*, 49(2), 159-177. <https://doi.org/10.1016/j.qref.2007.04.002>
- Chuang, K.-S. (2014). Financial advisors, financial crisis, and shareholder wealth in bank mergers. *Global Finance Journal*, 25(3), 229-245. <https://doi.org/10.1016/j.gfj.2014.10.004>
- Depamphilis, D. M. ; (2014). *MERGERS, ACQUISITIONS, AND OTHER RESTRUCTURING ACTIVITIES: AN INTEGRATED APPROACH PROCESS, TOOLS, CASES, AND SOLUTIONS* (Oxford). Academic Press. [//rlc-mm.feb.ui.ac.id%2Findex.php%3Fp%3Dshow_detail%26id%3D7105%26keywords%3D](https://rlc-mm.feb.ui.ac.id%2Findex.php%3Fp%3Dshow_detail%26id%3D7105%26keywords%3D)
- Diamond, P. A., & Maskin, E. (1981). An equilibrium analysis of search and breach of contract II. A non-steady state example. *Journal of Economic Theory*, 25(2), 165-195. [https://doi.org/10.1016/0022-0531\(81\)90001-6](https://doi.org/10.1016/0022-0531(81)90001-6)
- Duchin, R., & Schmidt, B. (2013). Riding the merger wave: Uncertainty, reduced monitoring, and bad acquisitions. *Journal of Financial Economics*, 107(1), 69-88. <https://doi.org/10.1016/j.jfineco.2012.07.003>

- Ertugrul, M., & Krishnan, K. (2014). Investment Banks in Dual Roles: Acquirer M&a Advisors as Underwriters. *Journal of Financial Research*, 37(2), 159-189. <https://doi.org/10.1111/jfir.12033>
- Golubov, A., Petmezas, D., & Travlos, N. G. (2012). When It Pays to Pay Your Investment Banker: New Evidence on the Role of Financial Advisors in M&As. *The Journal of Finance*, 67(1), 271-311. <https://doi.org/10.1111/j.1540-6261.2011.01712.x>
- Ismail, A. (2010). *Are Good Financial Advisors Really Good? The Performance of Investment Banks in the M&A Market* (SSRN Scholarly Paper 1154532). <https://doi.org/10.2139/ssrn.1154532>
- Kale, J. R., Kini, O., & Ryan, H. E. (2003). Financial Advisors and Shareholder Wealth Gains in Corporate Takeovers. *The Journal of Financial and Quantitative Analysis*, 38(3), 475-501. <https://doi.org/10.2307/4126728>
- Loyeung, A. (2019). The role of boutique financial advisors in mergers and acquisitions. *Australian Journal of Management*, 44(2), 212-247. <https://doi.org/10.1177/0312896218792970>
- MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, 35(1), 13-39.
- McCombie, D. W. (2022, november 15). *The ROI Of Hiring An Investment Banker*. Forbes. <https://www.forbes.com/sites/davidwmccombie/2022/11/15/the-roi-of-hiring-an-investment-banker/>
- McLaughlin, R. M. (1992). Does the form of compensation matter?: Investment banker fee contracts in tender offers. *Journal of Financial Economics*, 32(2), 223-260. [https://doi.org/10.1016/0304-405X\(92\)90019-T](https://doi.org/10.1016/0304-405X(92)90019-T)
- Mortensen, D. T. (1982). The Matching Process as a Noncooperative Bargaining Game. In *The Economics of Information and Uncertainty* (pp. 233-258). University of Chicago Press. <https://www.nber.org/books-and-chapters/economics-information-and-uncertainty/matching-process-noncooperative-bargaining-game>
- Nguyen, H. T. D., & Tsai, H. (2024). Relationship Advisors Guiding Financially Weak Targets in M&A Deals: Conflict of Interest and Reputation Concerns. *Finance Research Letters*, 61, 105013. <https://doi.org/10.1016/j.frl.2024.105013>
- O'Brien, G. (2024, januari 19). *European financial services M&A deal volume fell in 2023, and total deal value hit a decade-low*. https://www.ey.com/en_gl/news/2024/01/european-financial-

services-m-a-deal-volume-fell-in-2023-and-total-deal-value-hit-a-decade-

low#:~:text=The%20European%20financial%20services%20industry,EY%20financial%20services%20M%26A%20analysis.

Raghavendra Rau, P. (2000). Investment bank market share, contingent fee payments, and the performance of acquiring firms. *Journal of Financial Economics*, 56(2), 293-324. [https://doi.org/10.1016/S0304-405X\(00\)00042-8](https://doi.org/10.1016/S0304-405X(00)00042-8)

Schiereck, D., Sigl-Grüb, C., & Unverhau, J. (2009). Investment bank reputation and shareholder wealth effects in mergers and acquisitions. *Research in International Business and Finance*, 23(3), 257-273. <https://doi.org/10.1016/j.ribaf.2008.09.004>

Servaes, H., & Zenner, M. (1996). The Role of Investment Banks in Acquisitions. *Review of Financial Studies*, 9(3), 787-815. <https://doi.org/10.1093/rfs/9.3.787>

Shapiro, C. (1983). Premiums for High Quality Products as Returns to Reputations. *The Quarterly Journal of Economics*, 98(4), 659-679. <https://doi.org/10.2307/1881782>

Song, W., Wei, J. (Diana), & Zhou, L. (2013). The value of “boutique” financial advisors in mergers and acquisitions. *Journal of Corporate Finance*, 20, 94-114. <https://doi.org/10.1016/j.jcorpfin.2012.12.003>

Walter, T. S., Yawson, A., & Yeung, C. P. W. (2008). The role of investment banks in M&A transactions: Fees and services. *Pacific-Basin Finance Journal*, 16(4), 341-369. <https://doi.org/10.1016/j.pacfin.2007.08.002>

Wang, C., Xie, F., & Zhang, K. (2020). *Expert Advice: Industry Expertise of M&A Advisors and Acquirer Shareholder Returns* (SSRN Scholarly Paper 3667869). <https://doi.org/10.2139/ssrn.3667869>

7 Appendix

TABLE 6: DESCRIPTION OF VARIABLES

Variable	Measurement	Source
Dependent variable		
CAR_{i,t_1,t_2}	The average cumulative abnormal returns for the acquiring firm from day t-1 to day t+1, where t is the completed date of the deal.	LSEG
Independent variables		
<i>FINADV</i>	The ranking of the first listed announced financial advisor in a deal on the league ranking table of European financial advisors	Orbis M&A & LSEG
<i>COMPLEXITYSCALE</i>	Sum of all suggested complexity dummies, which are <i>DEALVALUEDUMMY</i> , <i>MULTIPLEBIDDERS</i> , <i>DEALTYPE</i> , <i>FORMOFPAYMENT</i> , <i>CRISIS</i> , <i>MERGERWAVES</i> .	LSEG
<i>DEALVALUEDUMMY</i>	Dummy variable which is equal to 1 if the deal value is above the average of all deal values in the sample.	LSEG
<i>MULTIPLEBIDDERS</i>	Dummy variable which is equal to 1 if the deal had multiple bidders. Estimated with another sample which also included the not completed deals.	Orbis M&A
<i>DEALTYPE</i>	Dummy variable which is equal to 1 if the deal is hostile.	Orbis M&A
<i>FORMOFPAYMENT</i>	Dummy variable which is equal to 1 if the deal is financed by any other method than cash or mixed.	Orbis M&A
<i>CRISIS</i>	Dummy variable which is equal to 1 if the deal is completed in the years 2007-2009 or 2020.	Orbis M&A
<i>MERGERWAVES</i>	Dummy variable which is equal to 1 if the deal is completed in the year 2003-2007.	Orbis M&A
Control variables		
<i>ACQUISITION EXPERIENCE</i>	The number of deals the financial advisor has advised before the completed date of the deal in the sample.	Orbis M&A

<i>ACQEXPERIENCE</i>	The number of deals the acquiror has performed before the completed date of the deal in the sample.	Orbis M&A
<i>TAREXPERIENCE</i>	The number of deals the target has performed before the completed date of the deal in the sample.	Orbis M&A
<i>logSIZE</i>	The logarithm of the size of the acquiror of the deal	LSEG
<i>CROSSBORDER</i>	Dummy variable which is equal to 1 if the deal is acquiring firm is in a different country than the target firm.	Orbis M&A

Table 6 shows a description of all variables in the analyses and the sources where the data has been retrieved from.

TABLE 7: RANKING OF THE FINANCIAL ADVISORS

Advisor	Ranking				
Goldman Sachs & Co	1	Societe Generale	16	SEB	29
Morgan Stanley	2	PJT Partners Inc	17	Global Leisure Partners LLP	30
UBS	3	Peel Hunt LLP	18	Nomura	31
JP Morgan	4	Moelis & Co	19	Eastdil Secured LLC	32
Barclays	5	PricewaterhouseCoopers	20	N1 Singer Ltd	33
Centerview Partners LLC	6	Santander Corp & Invest Bkg	21	Wells Fargo & Co	34
Citi	7	Deloitte	22	KPMG	35
Lazard	8	Houlihan Lokey	23	Robert W Baird & Co Inc	36
BofA Securities Inc	9	Macquarie Group	24	Daiwa Securities Group Inc	37
Deutsche Bank	10	Credit Agricole CIB	25	Shot Tower Capital LLC	38
BNP Paribas SA	11	Canaccord Genuity Grp Inc	26	RedBird BD LLC	39
Jefferies LLC	12	HSBC Holdings PLC	27	Akur Ltd	40
Rothschild & Co	13	Natixis	28	RBC Capital Markets	41*
Evercore Inc	14				
Mediobanca	15				

Sumitomo Mitsui Finl Grp Inc	41*
Banca Akros SpA/Oaklins Italy	43
IMI - Intesa Sanpaolo	44
LionTree Advisors LLC	45
Oaklins	46
CIBC World Markets Inc	47
Qatalyst Partners	48
Lilja & Co AG	49*
Sure Advisory Srl	49*
Mizuho Financial Group	51
Raymond James Financial Inc	52
Jones Lang LaSalle Inc	53
Carnegie Investment Bank AB	54
Ernst & Young LLP	55
FIH Partners AS	56
ABG Sundal Collier	57*

DNB ASA	57*
Fearnley Fonds A/S	57*
Finint Corporate Advisors Srl	60
Four Partners Advisory SIM SpA	61
Savills PLC	62
Vitale&Co-IMAP	63
Ardea Partners Llc	64*
Oppenheimer Holdings Inc	64*
IMAP	66
Baker Tilly International	67
BrightTower LLC	68
Stifel/KBW	69
Clearwater International	70
Altus Capital Ltd	71*
ING	71*
Aream & Co	73*
Octagon Capital Corp	73*
Lincoln International	75
Global M&A	76

KeyBanc Capital Markets Inc	77
Duff & Phelps,A Kroll Business	78
ICECAPITAL Securities Ltd	79
Equita SIM SpA	80
Banco BTG Pactual SA	81
UniCredit	82
William Blair & Co	83
Allen & Co Inc	84
Craig-Hallum, Inc.	85*
Imperial Credit Industries Inc	85*
TD Securities Inc	87
Credito Emiliano	88
Intermonte SIM SpA	89
Gleacher Shacklock LLP	90
AZ Capital	91
Danske Bank	92
SPARK Advisory Partners Ltd	93

Sage Group LLC	94
EFG Hermes	95
finnCap Ltd	96
Marathon Capital LLC	97
Strand Hanson Ltd	98
Pareto AS	99
Lenner & Partners	100
Clairfield International	101
Bryan, Garnier & Co	102
Acuity Advisors Ltd	103
HLP Corporate Finance Oy	104
Grant Thornton	105
China International Capital Co	106
Bluefield Partners LLP	107*
Mazars SA	107*
Samsung Securities	109
Panmure Gordon & Co Ltd	110
RSM Corporate Fin LLP	111

IPOPEMA Securities SA	112
Integrae SIM SpA	113*
Investis Advisory Srl	113*
Translink Corporate Finance	115
Denton	116*
Grant Thornton Frackowiak	116*
IA Global Capital Ltd	116*
Fort Capital Corp	119
Svalner Skatt & Transaktion KB	120
Redeye AB	121
Piper Sandler & Co	122
Prometeia SpA	123
Cooper Parry Corporate Finance	124
Capitalmind Investec	125
Shore Capital Group	126
M & A Worldwide	127

Ernst & Young Audyt Polska	128
Norgestion	129
Cowgill Holloway LLP	130
MANGOLD FONDKOMISSI ON AB	131
Tech Hldg Intl Inc	132
CFI	133
FTI Consulting Inc	134
CBRE Group Inc	135
Oddo BHF SCA	136
Clipperton Finance SARL	137
Aegis Group PLC	138
RSM International Ltd	139
Globalscope	140
Agentis Capital	141
Beskidzki Dom Marklerski {BDM}	142
Banco BPM SpA	143

Vastra Hamn Fondkommission AB	144
Nordea	145
GCG	146
Benchmark International	147
Hoodless Brennan & Partners	148
Beaumont Cornish	149
WH Ireland Ltd	150
Panmure Gordon (UK) Ltd	151
Liberum Capital	152
Vator Securities AB	153
Cairn Financial Advisers Ltd	154
Other	155

TABLE 8 CORRELATION MATRIX

	DEALVAL UE	FORMOPF AYMENT	CROSSBO RDER	DEALTYP E	ACQUISIT IONEXPE RIENCE	ACQEXPE RIENCE	TAREXPE RIENCE	MULTIPL EBIDDER S	SIZE	CAR
DEALVAL UE	1	-0.006	0.094	-0.006	0.047	-0.005	0	0.044	0.411	-0.014
FORMOPF AYMENT	-0.048	1	-0.077	-0.071	0.074	0.010	0.007	-0.025	-0.026	-0.004
CROSSBO RDER	0.338	-0.077	1	-0.014	0.001	-0.068	-0.010	0.019	0.224	-0.033
DEALTYP E	0.011	-0.071	-0.014	1	-0.026	-0.018	-0.023	0.019	-0.014	-0.018
ACQUISIT IONEXPE RIENCE	0.026	0.068	-0.008	-0.032	1	0.162	0.228	-0.009	0.037	-0.021
ACQEXPE RIENCE	-0.033	-0.002	-0.034	-0.023	0.198	1	0.358	0.015	0.070	0.007
TAREXPE RIENCE	-0.020	0.022	-0.015	-0.028	0.187	0.650	1	-0.012	0.039	-0.021
MULTIPL EBIDDER S	0.074	-0.025	0.019	0.019	0.002	-0.006	-0.011	1	0.017	-0.002
SIZE	0.760	-0.067	0.366	0.019	0.019	0.097	-0.014	0.056	1	-0.053
CAR	-0.048	-0.003	-0.030	-0.024	-0.016	-0.013	-0.023	-0.004	-0.059	1
FINADV	-0.498	0.063	-0.213	-0.027	-0.056	0.005	0.004	-0.035	-0.490	0.016
CRISIS	0.015	-0.028	0.011	-0.027	-0.015	0.088	0.140	0.023	-0.021	-0.005
MERGER WAVES	0.044	-0.069	-0.007	-0.026	-0.021	0.208	0.357	-0.015	0.011	-0.046
Dummy target advisor in league table	0.401	-0.025	0.145	0.013	0.026	0.002	-0.001	0.041	0.309	-0.034

Target	-0.408	0.027	-0.152	-0.011	-0.026	-0.002	0.001	-0.041	-0.317	0.035
	FINADV	CRISIS	MERGERWAVES	DUMNYTA RADV	TARADV	SIC	logSIZE	logDEA LVALU E	DEALV ALUED UMNY	COMPL EXITYS CALE
DEALVAL UE	-0.227	0.030	0.012	0.312	-0.338	-0.096	0.316	0.457	0.447	0.236
FORMOP AYMENT	0.062	-0.028	-0.069	-0.025	0.031	0.022	-0.066	-0.049	-0.039	0.369
CROSSBO RDER	-0.227	0.011	-0.007	0.145	-0.162	-0.191	0.365	0.331	0.188	0.059
DEALTYP E	-0.030	-0.027	-0.026	0.013	-0.007	-0.027	0.016	0.009	0.006	0.019
ACQUISIT IONEXPER IENCE	-0.042	-0.013	-0.007	0.016	-0.019	-0.013	0.023	0.036	0.050	0.042
ACQEXPE RIENCE	0.063	0.027	0.064	-0.031	0.028	0.088	0.048	-0.116	-0.030	0.037
TAREXPE RIENCE	-0.039	0.137	0.329	0.007	-0.011	-0.043	0.020	-0.013	-0.021	0.216
MULTIPLE BIDDERS	-0.033	0.023	-0.015	0.041	-0.043	-0.036	0.054	0.077	0.064	0.263
SIZE	-0.309	0.030	0.028	0.267	-0.290	-0.179	0.610	0.460	0.413	0.212
CAR	0.025	-0.006	-0.035	-0.033	0.032	0.031	-0.069	-0.056	-0.034	-0.039
FINADV 1	0.007	0.007	0.009	-0.255	0.273	0.133	-0.523	-0.541	-0.407	-0.164
CRISIS	0.009	1	0.177	0.007	-0.012	-0.024	-0.014	0.018	0.021	0.586
MERGER WAVES	0.026	0.177	1	0.019	-0.028	-0.030	0.015	0.038	-0.003	0.534
DUMNYT ARADV	-0.249	0.007	0.019	1	-0.972	-0.097	0.317	0.437	0.431	0.213
TARADV	0.256	-0.010	-0.022	-0.997	1	0.095	-0.341	-0.458	-0.459	-0.230
SIC	0.151	-0.019	-0.034	-0.103	0.104	1	-0.203	-0.218	-0.118	-0.082
logSIZE	-0.490	-0.021	0.011	0.309	-0.317	-0.218	1	0.756	0.519	0.226
logDEALV	-0.498	0.015	0.044	0.401	-0.408	-0.238	0.760	1	0.703	0.351
COMPLEX ITYSCALE	-0.159	0.568	0.512	0.206	-0.214	-0.092	0.211	0.319	0.463	1

TABLE 9: VARIATION INFLATION FACTOR

VAR	VIF
FINADV	1.495
FORMOFPAYMENT	1.026
CROSSBORDER	1.176
DEALTYPE	1.009
ACQUISITIONEXPERIENCE	1.083
ACQEXPERIENCE	1.244
TAREXPERIENCE	1.361
MULTIPLEBIDDERS	1.009
CRISIS	1.045
MERGERWAVES	1.168
logSIZE	1.618
logDEALVALUE	2.677

Table 9 shows the variation inflation factor of all variables in our first estimated model, the VIF measure shows no abnormalities and suggests no multicollinearity in the model.

TABLE 10: DURBIN WATSON TEST FOR AUTOCORRELATION

Durbin-Watson	
Model 1	p-value
1.9753	0.48
Model 2	
1.9796	0.734
Model 3	
1.9798	0.788

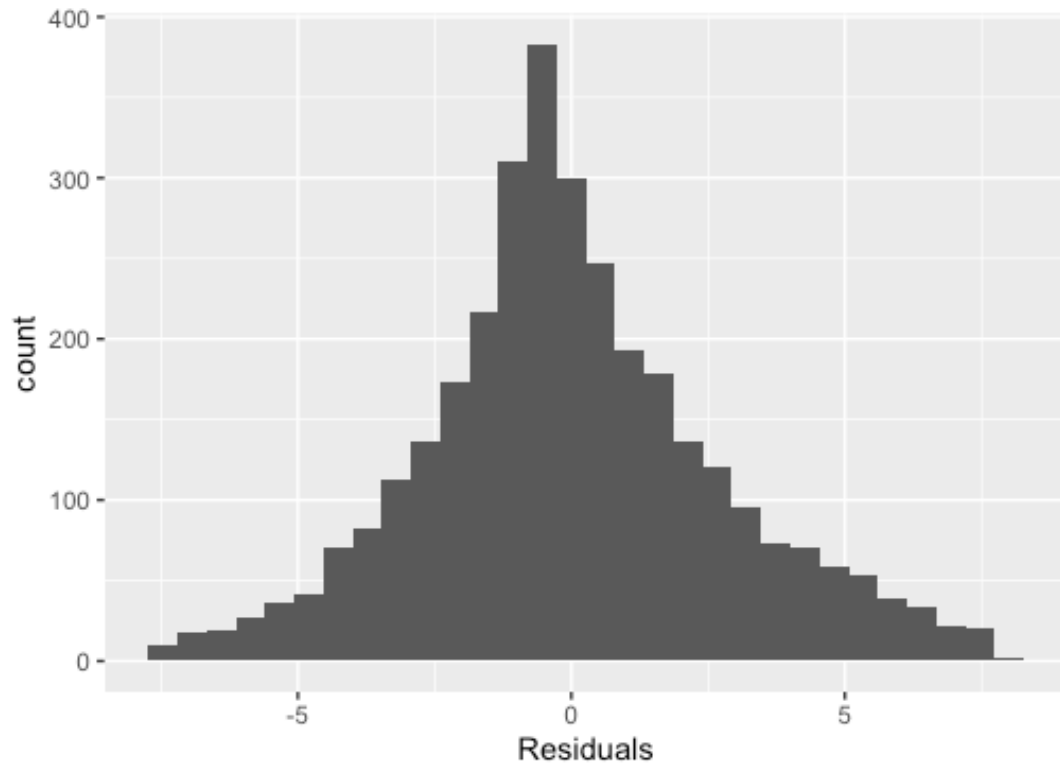
Table 10 shows the results of the Durbin Watson test of the full sample three models suggested in the methodology. The three DW statistics are all around 2 which states that there is no autocorrelation in the model.

TABLE 11: BREUSCH-PAGAN TEST FOR HETEROSKEDASTICITY

Breusch-Pagan	
Model 1	p-value
99.963	0.000
Model 2	
81.125	0.000
Model 3	
81.411	0.000

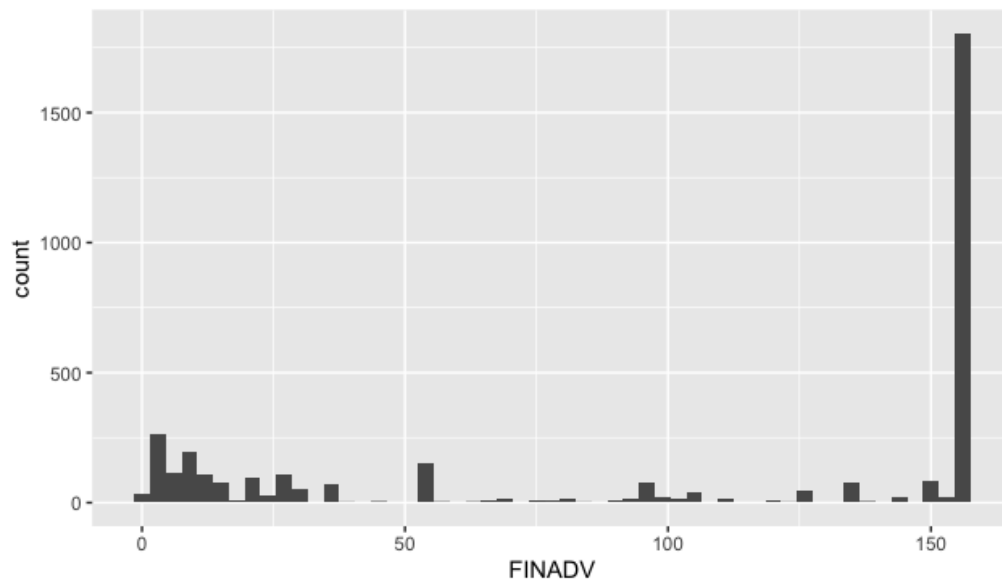
Table 11 shows the results of the Breusch-Pagan test of the full sample three models suggested in the methodology. The three BP test show no significant results which indicates that there is no heteroskedasticity.

GRAPH 2: HISTOGRAM OF RESIDUALS OF MODEL 1



Graph 2 shows the residuals of model 1. The histogram is normally distributed.

GRAPH 3: HISTOGRAM OF THE RANKING OF THE FINANCIAL ADVISORS



Graph 3 shows the number of financial advisors that are ranked at a certain ranking. There is a spike at 155 because these are the financial advisors that are not ranked on this ranking.

TABLE 12: INDUSTRY DIVIDED

Industry	Number of deals
Construction	111
Finance, Insurance and Real Estate	573
Manufacturing	1014
Mining	165
Public Administration	4
Retail Trade	178
Services	1152
Transportation, Communications, Electric, Gas and Sanitary Service	388
Wholesale Trade	72

TABLE 13: SEPARATE MODELS

	CAR					
	(1)	(Top)	(Middle)	(Low)	(5)	(6)
FINADV	0.001 (0.001)	-0.005 (0.027)	0.0004 (0.009)	-0.014** (0.006)		
logDEALVALUE					-0.066*** (0.021)	
FORMOFPAYMENT					-0.081 (0.130)	
DEALTYPE					-0.972** (0.469)	
MULTIPLEBIDDERS					0.025 (0.267)	
CRISIS					0.004 (0.129)	
MERGERWAVES					-0.248** (0.121)	
CROSSBORDER						-0.045 (0.103)
ACQUISITIONEXPERIENCE						-0.002 (0.002)
ACQEXPERIENCE						0.014 (0.012)
TAREXPERIENCE						-0.108 (0.087)
logSIZE						-0.075*** (0.021)
Constant	0.341*** (0.080)	0.228 (0.191)	0.477* (0.283)	2.412*** (0.678)	1.270*** (0.263)	1.530*** (0.285)
N	3278	713	496	461	3278	3278
R ²	0.001	0.0004	0.000	0.014	0.005	0.006
Adjusted R ²	0.0003	-0.001	-0.002	0.012	0.003	0.004
Residual std error	2.759	2.409	2.726	2.888	2.756	2.754
F	2.125	0.030	0.002	6.547**	2.552***	3.806***

Table 13 presents the OLS regression on CAR (-1,+1). The first column is the full sample with only the ranking of the financial advisors, the top, middle and low columns are the different tiers specified in the methodology with only the ranking of the financial advisors. The fifth model is only with the complexity variables on the full sample and the sixth models is only with the control variables. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

TABLE 14: WITH AND WITHOUT TARGET ADVISORS

	CAR					
	(1) With	(1) Without	(2) With	(2) Without	(3) With	(3) Without
FINADV	0.001 (0.002)	-0.001 (0.001)	0.0001 (0.002)	-0.001 (0.001)		
logDEALVALUE	0.045 (0.114)	-0.006 (0.038)				
FORMOFPAYMENT	0.182 (0.364)	-0.119 (0.141)				
COMPLEXITYSCALE			-0.249 (0.160)	-0.051 (0.067)		
FINADV_centered					0.0003 (0.003)	-0.001 (0.001)
COMPLEXITYSCALE_centered					-0.280 (0.189)	-0.051 (0.068)
CROSSBORDER	-0.198 (0.311)	-0.039 (0.111)	-0.266 (0.308)	-0.031 (0.110)	-0.269 (0.309)	-0.031 (0.110)
DEALTYPE	0.572 (2.499)	-1.306*** (0.433)				
ACQUISITIONEXPERIENCE	0.003 (0.005)	-0.003 (0.002)	0.004 (0.005)	-0.002 (0.002)	0.003 (0.005)	-0.002 (0.002)
ACQEXPERIENCE	0.009 (0.060)	0.014 (0.013)	-0.007 (0.061)	0.016 (0.013)	-0.008 (0.061)	0.016 (0.013)
TAREXPERIENCE	0.114 (0.261)	-0.089 (0.102)	0.032 (0.247)	-0.112 (0.097)	0.032 (0.247)	-0.112 (0.097)
MULTIPLEBIDDERS	-0.079 (0.677)	0.009 (0.295)				
logSIZE	0.046 (0.111)	-0.093*** (0.034)	0.098 (0.091)	-0.096*** (0.026)	0.101 (0.092)	-0.096*** (0.026)
CRISIS	-0.362 (0.358)	0.039 (0.139)				
MERGERWAVES	-0.541 (0.375)	-0.186 (0.139)				
FINADV_centered: COMPLEXITYSCALE_centered					-0.001 (0.002)	0.00005 (0.001)
Constant	-1.156 (1.535)	2.086*** (0.448)	-0.521 (1.415)	2.047*** (0.419)	-1.152 (1.359)	1.821*** (0.360)
N	397	2881	397	2881	397	2881
R ²	0.015	0.008	0.010	0.007	0.010	0.007
Adjusted R ²	-0.016	0.004	-0.008	0.005	-0.010	0.005
Residual std error	2.704	2.763	2.694	2.762	2.697	2.763
F	0.485	2.032**	0.553	3.012***	0.495	2.635***

Table 14 presents the OLS regression on CAR (-1,+1). All columns are the full sample, the first two columns are model 1, in the first column all deals with target advisor in the ranking are listed and in the second without a ranked adviser The third and fourth is the same but for model 2 and the fifth and sixth columns are model 3. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

TABLE 15: MODEL 1 LONG TERM CAR

	longCAR			
	(Full)	(Top)	(Middle)	(Low)
FINADV	0.0005 (0.002)	0.006 (0.005)	-0.002 (0.007)	-0.005 (0.007)
logDEALVALUE	-0.119 (0.098)	-0.065 (0.198)	-0.016 (0.273)	-0.203 (0.260)
FORMOFPAYMENT	-0.111 (0.396)	-0.440 (0.776)	1.059 (1.071)	-0.039 (1.119)
CROSSBORDER	-0.351 (0.302)	0.025 (0.604)	0.026 (0.805)	-0.302 (0.826)
DEALTYPE	0.766 (2.805)	6.427 (5.307)	-4.678 (3.278)	-0.783 (1.580)
ACQUISITIONEXPERIENCE	-0.009* (0.005)	-0.004 (0.009)	-0.019 (0.014)	-0.038*** (0.014)
ACQEXPERIENCE	0.059 (0.040)	0.099 (0.094)	-0.064 (0.091)	-0.098 (0.099)
TAREXPERIENCE	0.130 (0.272)	-0.467 (0.579)	0.837 (0.735)	-0.776 (0.683)
MULTIPLEBIDDERS	0.291 (0.755)	-2.161 (1.502)	3.509 (2.298)	1.203 (2.294)
logSIZE	0.033 (0.092)	0.048 (0.193)	-0.279 (0.252)	0.361 (0.260)
CRISIS	-0.147 (0.380)	-0.650 (0.705)	-1.818 (1.129)	0.626 (0.936)
MERGERWAVES	-1.000*** (0.369)	-0.543 (0.655)	0.141 (1.007)	-1.892* (1.072)
Constant	1.134 (1.167)	0.010 (2.525)	3.461 (3.216)	0.064 (3.185)
N	3378	775	509	463
R2	0.006	0.015	0.023	0.044
Adjusted R2	0.002	-0.001	-0.001	0.018
Residual std error	8.058	7.451	8.488	8.247
F	1.695*	0.943	0.968	1.710*

Table 15 presents the OLS regression on the long term CAR (-1,+20). This is again model 1, where column 1 is the full sample and the other three columns the tiers as specified in the methodology. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

TABLE 16: MODEL 2 LONG TERM CAR

	longCAR			
	(Full)	(Top)	(Middle)	(Low)
FINADV	0.001 (0.002)	0.005 (0.005)	-0.001 (0.007)	-0.005 (0.007)
COMPLEXITYSCALE	-0.428** (0.176)	-0.731** (0.318)	-0.047 (0.445)	-0.413 (0.499)
ACQUISITIONEXPERIENCE	-0.009* (0.005)	-0.003 (0.009)	-0.016 (0.014)	-0.036*** (0.014)
ACQEXPERIENCE	0.071* (0.038)	0.091 (0.089)	-0.060 (0.089)	-0.063 (0.092)
TAREXPERIENCE	-0.006 (0.258)	-0.430 (0.535)	0.741 (0.707)	-1.160* (0.674)
CROSSBORDER	-0.380 (0.299)	-0.122 (0.590)	-0.111 (0.790)	-0.296 (0.830)
logSIZE	-0.015 (0.071)	0.069 (0.154)	-0.245 (0.192)	0.274 (0.195)
Constant	0.855 (1.089)	-0.557 (2.421)	3.600 (2.922)	-0.420 (3.057)
N	3378	775	509	463
R2	0.005	0.012	0.009	0.037
Adjusted R2	0.003	0.003	-0.005	0.022
Residual std error	8.057	7.435	8.507	8.231
F	2.362**	1.373	0.614	2.480***

Table 16 presents the OLS regression on the long term CAR (-1,+20). This is again model 2, where column 1 is the full sample and the other three columns the tiers as specified in the methodology. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

TABLE 17: MODEL 3 LONG TERM CAR

	longCAR			
	(Full)	(Top)	(Middle)	(Low)
FINADV_centered	0.001 (0.002)	0.006 (0.005)	-0.001 (0.007)	-0.005 (0.007)
COMPLEXITYSCALE_centered	-0.416** (0.182)	-0.762** (0.346)	-0.210 (0.515)	-0.393 (0.488)
ACQUISITIONEXPERIENCE	-0.009* (0.005)	-0.003 (0.009)	-0.017 (0.014)	-0.036*** (0.014)
ACQEXPERIENCE	0.072* (0.038)	0.090 (0.089)	-0.075 (0.091)	-0.064 (0.092)
TAREXPERIENCE	-0.014 (0.259)	-0.419 (0.541)	0.810 (0.714)	-1.154* (0.672)
CROSSBORDER	-0.379 (0.299)	-0.123 (0.592)	-0.111 (0.791)	-0.320 (0.835)
logSIZE	-0.013 (0.071)	0.069 (0.154)	-0.246 (0.193)	0.269 (0.194)
FINADV_centered: COMPLEXITYSCALE_centered	0.001 (0.002)	-0.001 (0.004)	-0.007 (0.006)	-0.002 (0.007)
Constant	0.291 (0.969)	-1.055 (2.200)	3.337 (2.635)	-1.446 (2.602)
N	3378	775	509	463
R2	0.005	0.012	0.011	0.037
Adjusted R2	0.003	0.002	-0.005	0.020
Residual std error	8.058	7.440	8.506	8.239
F	2.093**	1.206	0.674	2.4176**

Table 17 presents the OLS regression on the long term CAR (-1,+20). This is again model 3, where column 1 is the full sample and the other three columns the tiers as specified in the methodology. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

TABLE 18: MODELS WITH YEAR DUMMIES

	CAR		
	(1)	(2)	(3)
FINADV	-0.001 (0.001)	-0.001 (0.001)	
logDEALVALUE	0.002 (0.034)		
FORMOFPAYMENT	-0.101 (0.132)		
COMPLEXITYSCALE		-0.045 (0.090)	
FINADV_centered			-0.001 (0.001)
COMPLEXITYSCALE_centered			-0.042 (0.092)
CROSSBORDER	-0.030 (0.104)	-0.025 (0.104)	-0.025 (0.103)
DEALTYPE	-0.877* (0.518)		
ACQUISITIONEXPERIENCE	-0.003* (0.002)	-0.003* (0.002)	-0.003* (0.002)
ACQEXPERIENCE	0.013 (0.013)	0.013 (0.012)	0.013 (0.012)
TAREXPERIENCE	0.084 (0.102)	0.083 (0.102)	0.083 (0.102)
MULTIPLEBIDDERS	0.024 (0.269)		
logSIZE	-0.089*** (0.033)	-0.084*** (0.025)	-0.084*** (0.025)
CRISIS	-0.240 (0.368)		
MERGERWAVES	-1.476** (0.595)		
factor(jaar)2004	0.617 (0.585)	0.624 (0.586)	0.624 (0.565)
factor(jaar)2005	0.596 (0.563)	0.597 (0.566)	0.596 (0.545)
factor(jaar)2006	1.008* (0.548)	1.010* (0.551)	1.009* (0.529)
factor(jaar)2007	1.099* (0.653)	0.910* (0.549)	0.905* (0.528)
factor(jaar)2008	-0.405	0.838	0.838

	(0.341)	(0.569)	(0.548)
factor(jaar)2009	-0.267	0.968	0.969*
	(0.388)	(0.597)	(0.576)
factor(jaar)2010	-0.768**	0.650	0.653
	(0.385)	(0.574)	(0.553)
factor(jaar)2011	-0.821**	0.604	0.607
	(0.358)	(0.558)	(0.537)
factor(jaar)2012	-0.137	1.286**	1.288**
	(0.382)	(0.576)	(0.554)
factor(jaar)2013	-0.528	0.893	0.895
	(0.389)	(0.579)	(0.557)
factor(jaar)2014	-0.782**	0.639	0.642
	(0.365)	(0.563)	(0.541)
factor(jaar)2015	-0.359	1.071*	1.075**
	(0.357)	(0.559)	(0.538)
factor(jaar)2016	-0.209	1.213**	1.217**
	(0.358)	(0.560)	(0.538)
factor(jaar)2017	-0.578*	0.851	0.855
	(0.347)	(0.554)	(0.532)
factor(jaar)2018	-0.400	1.032*	1.036*
	(0.347)	(0.556)	(0.534)
factor(jaar)2019	-0.111	1.314**	1.317**
	(0.344)	(0.557)	(0.536)
factor(jaar)2020		1.236**	1.235**
		(0.566)	(0.545)
factor(jaar)2021	-0.211	1.213**	1.217**
	(0.346)	(0.560)	(0.539)
factor(jaar)2022	-0.159	1.271**	1.275**
	(0.357)	(0.568)	(0.547)
factor(jaar)2023		1.424**	1.428**
		(0.605)	(0.585)
FINADV_centered:COMPLEXITYSCALE_centered			0.0002
			(0.001)
Constant	2.207***	0.752	0.558
	(0.501)	(0.656)	(0.581)
N	3278	3278	3278
R2	0.014	0.014	0.014
Adjusted R2	0.005	0.006	0.006
Residual std error	2.753	2.752	2.752
F	1.580**	1.711**	1.650**

Table 18 presents the OLS regression on the CAR (-1,+1). All columns are the full sample, and every column is one of the suggested models elaborated in the methodology. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

TABLE 19: MODEL WITH INDUSTRY DUMMIES

	CAR		
	(1)	(2)	(3)
FINADV	-0.001 (0.001)	-0.001 (0.001)	
logDEALVALUE	-0.007 (0.035)		
FORMOFPAYMENT	-0.066 (0.131)		
COMPLEXITYSCALE		-0.067 (0.061)	
FINADV_centered			-0.001 (0.001)
COMPLEXITYSCALE_centered			-0.066 (0.062)
CROSSBORDER	-0.070 (0.109)	-0.066 (0.108)	-0.066 (0.108)
DEALTYPE	-0.982** (0.496)		
ACQUISITIONEXPERIENCE	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
ACQEXPERIENCE	0.015 (0.013)	0.016 (0.013)	0.016 (0.013)
TAREXPERIENCE	-0.053 (0.094)	-0.082 (0.090)	-0.083 (0.090)
MULTIPLEBIDDERS	0.016 (0.268)		
logSIZE	-0.076** (0.034)	-0.077*** (0.026)	-0.077*** (0.026)
CRISIS	0.007 (0.130)		
MERGERWAVES	-0.215* (0.130)		
SIC_Division_Construction	-0.203 (0.318)	-0.205 (0.318)	-0.205 (0.318)
`SIC_Division_Finance, Insurance and Real Estate`	0.010 (0.148)	0.022 (0.147)	0.022 (0.147)

SIC_Division_Mining	-0.203 (0.287)	-0.185 (0.286)	-0.185 (0.286)
`SIC_Division_Public Administration`	3.537 (5.256)	3.528 (5.277)	3.531 (5.277)
`SIC_Division_Retail Trade`	-0.248 (0.234)	-0.252 (0.233)	-0.252 (0.233)
SIC_Division_Services	-0.020 (0.139)	-0.016 (0.138)	-0.015 (0.138)
`SIC_Division_Transportation, Communications, Electric, Gas and Sanitary service`	-0.187 (0.171)	-0.190 (0.170)	-0.190 (0.170)
`SIC_Division_Wholesale Trade`	0.015 (0.390)	0.009 (0.389)	0.010 (0.389)
FINADV_centered:COMPLEXITYSCALE_centered			0.0001 (0.001)
Constant	1.840*** (0.442)	1.846*** (0.420)	1.594*** (0.377)
N	3277	3277	3277
R2	0.009	0.008	0.008
Adjusted R2	0.003	0.004	0.004
Residual std error	2.755	2.754	2.755
F	1.519**	1.841**	1.726**

Table 19 presents the OLS regression on the CAR (-1,+1). All columns are the full sample, and every column is one of the suggested models elaborated in the methodology. Robust standard errors are incorporated in the brackets. *** p<0.01, p **p<0.05, * p<0.1

TABLE 20: BOUTIQUE AND FULL-SERVICE FULL SAMPLE

	CAR					
	(1) Bout.	(2) Bout.	(3) Bout.	(1) Full	(2) Full	(3) Full
FINADV	-0.001 (0.001)	-0.001 (0.001)		-0.0003 (0.001)	-0.001 (0.001)	
logDEALVALUE				0.052 (0.050)		
FORMOFPAYMENT	0.055 (0.182)			-0.205 (0.187)		
COMPLEXITYSCALE		-0.059 (0.090)			-0.097 (0.081)	
FINADV_centered			-0.001 (0.001)			-0.001 (0.001)
COMPLEXITYSCALE_centered			-0.056 (0.090)			-0.106 (0.086)
CROSSBORDER	-0.144 (0.150)	-0.153 (0.147)	-0.153 (0.147)	0.038 (0.147)	0.047 (0.146)	0.045 (0.146)
DEALTYPE	-1.038*** (0.380)			-1.187 (1.922)		
ACQUISITION EXPERIENCE	-0.0004 (0.002)	-0.0003 (0.002)	-0.0003 (0.002)	-0.004* (0.002)	-0.004 (0.002)	-0.004 (0.002)
ACQEXPERIENCE	0.001 (0.018)	0.006 (0.018)	0.006 (0.018)	0.027 (0.018)	0.023 (0.018)	0.023 (0.018)
TAREXPERIENCE	0.076 (0.141)	0.051 (0.134)	0.047 (0.135)	-0.187 (0.125)	-0.229* (0.118)	-0.226* (0.118)
logSIZE	-0.034 (0.046)	-0.065* (0.036)	-0.064* (0.036)	-0.138*** (0.046)	-0.098*** (0.034)	-0.099*** (0.035)
MULTIPLEBIDDERS	-0.148 (0.377)			0.098 (0.380)		
CRISIS	0.172 (0.186)			-0.205 (0.177)		
MERGERWAVES	-0.247 (0.184)			-0.234 (0.183)		
FINADV_centered: COMPLEXITYSCALE_centered			0.001 (0.001)			-0.001 (0.001)
Constant	1.635*** (0.580)	1.614*** (0.557)	1.363*** (0.480)	2.104*** (0.593)	2.176*** (0.545)	1.873*** (0.482)
N	1691	1691	1691	1578	1578	1578
R2	0.007	0.007	0.005	0.015	0.015	0.012
Adjusted R2	0.0004	0.0004	-0.0001	0.008	0.008	0.007
Residual std error	2.813	2.812	2.813	2.693	2.692	2.693
F	1.006	1.104	0.987	2.000***	2.820***	2.491***

Table 20 presents the OLS regression on the CAR (-1,+1). The first three columns are the boutique banks models of the full sample and the second three columns are the full service banks. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

TABLE 21: BOUTIQUE AND FULL-SERVICE TOP TIER

	CAR					
	(1) Boutique	(2) Boutique	(3) Boutique	(4) Full	(5) Full	(6) Full
FINADV	0.030 (0.047)	0.020 (0.047)		-0.008 (0.036)	-0.022 (0.036)	
logDEALVALUE				0.224*** (0.081)		
FORMOFPAYMENT				-0.530 (0.322)		
COMPLEXITYSCALE		-0.068 (0.163)			-0.152 (0.128)	
FINADV_centered			-0.025 (0.048)			-0.034 (0.037)
COMPLEXITYSCALE_centered			10.329** (4.779)			2.967 (3.191)
CROSSBORDER	0.304 (0.326)	0.226 (0.316)	0.199 (0.315)	0.353 (0.257)	0.302 (0.261)	0.299 (0.262)
DEALTYPE	-1.286** (0.631)			-0.477 (2.929)		
ACQUISITION EXPERIENCE	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)	-0.001 (0.004)	0.001 (0.004)	0.001 (0.004)
ACQEXPERIENCE	0.031 (0.058)	0.015 (0.057)	0.016 (0.055)	0.041 (0.050)	0.024 (0.051)	0.022 (0.052)
TAREXPERIENCE	0.302 (0.257)	0.291 (0.248)	0.264 (0.247)	-0.097 (0.229)	-0.230 (0.224)	-0.224 (0.227)
logSIZE	-0.097 (0.113)	-0.075 (0.099)	-0.060 (0.099)	-0.235** (0.099)	-0.098 (0.094)	-0.103 (0.094)
MULTIPLEBIDDERS				0.311 (0.559)		
CRISIS				-0.455 (0.301)		
MERGERWAVES				-0.338 (0.284)		
FINADV_centered: COMPLEXITYSCALE_centered			0.113** (0.051)			0.034 (0.035)
Constant	0.746 (1.528)	0.900 (1.467)	-1.664 (4.982)	1.385 (1.604)	2.218 (1.501)	-1.376 (3.703)
N	312	312	312	401	401	401
R2	0.033	0.018	0.033	0.046	0.015	0.017
Adjusted R2	-0.006	-0.005	0.008	0.017	-0.002	-0.003
Residual std error	2.503	2.502	2.486	2.320	2.342	2.343
F	0.838	0.776	1.301	1.563 *	0.870	0.852

Table 21 presents the OLS regression on the CAR (-1,+1). The first three columns are the boutique banks models of the full sample and the second three columns are the full service banks. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

TABLE 22: BOUTIQUE AND FULL-SERVICE MIDDLE TIER

	CAR					
	(1) Bout.	(2) Bout.	(3) Bout.	(1) Full	(2) Full	(3) Full
FINADV	-0.011 (0.014)	-0.011 (0.014)		0.010 (0.014)	0.010 (0.014)	
logDEALVALUE	-0.015 (0.127)			-0.077 (0.112)		
FORMOFPAYMENT	-0.412 (0.582)			-0.353 (0.464)		
COMPLEXITYSCALE		-0.185 (0.285)			0.141 (0.263)	
FINADV_centered			-0.012 (0.015)			0.010 (0.015)
COMPLEXITYSCALE_centered			-1.125 (1.777)			-0.017 (1.540)
CROSSBORDER	0.070 (0.398)	0.048 (0.382)	0.045 (0.383)	-0.153 (0.361)	-0.047 (0.356)	-0.049 (0.359)
DEALTYPE	-0.281 (0.842)					
ACQUISITIONEXPERIENCE	-0.008 (0.005)	-0.008 (0.005)	-0.008* (0.005)	0.001 (0.005)	-0.001 (0.005)	-0.001 (0.005)
ACQEXPERIENCE	0.012 (0.065)	0.007 (0.065)	0.007 (0.066)	-0.018 (0.057)	0.008 (0.055)	0.008 (0.055)
TAREXPERIENCE	0.041 (0.380)	0.118 (0.357)	0.113 (0.359)	-0.513* (0.279)	-0.534** (0.260)	-0.539** (0.271)
logSIZE	-0.053 (0.111)	-0.038 (0.092)	-0.036 (0.092)	-0.014 (0.113)	-0.068 (0.094)	-0.068 (0.094)
MULTIPLEBIDDERS	-1.231 (0.847)			2.927 (1.909)		
CRISIS	0.270 (0.596)			0.481 (0.551)		
MERGERWAVES	0.004 (0.527)			0.207 (0.493)		
FINADV_centered: COMPLEXITYSCALE_centered			-0.013 (0.025)			-0.002 (0.020)
Constant	2.292 (1.633)	1.994 (1.435)	0.334 (1.537)	1.659 (1.518)	1.003 (1.440)	2.336 (1.549)
N	254	254	254	242	242	242
R2	0.022	0.012	0.014	0.048	0.027	0.027
Adjusted R2	-0.027	-0.016	-0.018	0.003	-0.002	-0.007
Residual std error	2.882	2.866	2.869	2.584	2.591	2.597
F	0.450	0.437	0.448	1.065	0.919	0.802

Table 22 presents the OLS regression on the CAR (-1,+1). The first three columns are the boutique banks models of the full sample and the second three columns are the full service banks. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1

TABLE 23: BOUTIQUE AND FULL-SERVICE LOW TIER

	CAR					
	(1) Bout.	(2) Bout.	(3) Bout.	(1) Full	(2) Full	(3) Full
FINADV	-0.019	-0.018** (0.008)		-0.008 (0.009)	-0.009 (0.008)	
logDEALVALUE	-0.048			0.067 (0.178)		
FORMOFPAYMENT	0.452			0.413 (0.581)		
COMPLEXITYSCALE		0.259 (0.326)			-0.113 (0.301)	
FINADV_centered			-0.021** (0.009)			-0.013 (0.009)
COMPLEXITYSCALE_centered			0.495 (0.423)			0.240 (0.401)
CROSSBORDER	-0.924	-0.893** (0.428)	-0.884** (0.427)	-0.504 (0.483)	-0.504 (0.478)	-0.454 (0.480)
DEALTYPE	-2.284					
ACQUISITIONEXPERIENCE	-0.005	-0.004 (0.007)	-0.004 (0.006)	-0.019*** (0.006)	-0.017*** (0.006)	-0.017*** (0.006)
ACQEXPERIENCE	0.026	0.031 (0.042)	0.032 (0.042)	0.085 (0.059)	0.067 (0.055)	0.069 (0.051)
TAREXPERIENCE	0.119	-0.012 (0.364)	0.001 (0.362)	0.026 (0.355)	0.005 (0.336)	0.013 (0.331)
logSIZE	0.192	0.159 (0.109)	0.156 (0.108)	0.059 (0.157)	0.096 (0.112)	0.081 (0.111)
MULTIPLEBIDDERS	-0.179			-0.805 (0.806)		
CRISIS	0.281			-0.148 (0.493)		
MERGERWAVES	-0.276			-0.541 (0.649)		
FINADV_centered: COMPLEXITYSCALE_centered			-0.013 (0.015)			-0.017 (0.012)
Constant	1.201	0.847 (1.932)	-0.258 (1.357)	0.278 (2.129)	1.104 (2.025)	0.202 (1.400)
N	253	253	253	208	208	208
R2	0.055	0.051	0.056	0.067	0.058	0.064
Adjusted R2	0.008	0.024	0.025	0.014	0.025	-0.027
Residual std error	3.026	3.002	3.001	2.716	2.702	2.699
F	1.174	1.878*	1.803*	1.275	1.756*	1.711*

Table 23 presents the OLS regression on the CAR (-1,+1). The first three columns are the boutique banks models of the full sample and the second three columns are the full service banks. Robust standard errors are incorporated in the brackets. *** p<0.01, **p<0.05, * p<0.1