Do investment banks create value for their clients? Empirical evidence from European M&A

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Abstract

Top tier banks are associated with superior skills and service, demonstrated by the higher advisory fees they charge. The actual value they add to their clients, however, remains a widely debated topic. We provide new evidence on the question by extending existing empirical research to the European M&A market. We find that, while Tier 1 advisers (retained by either acquirer or target) increase target returns and deal premia, acquirers hiring Tier 1 advisers realize lower announcement returns than other bidders. Our results seem to support the deal completion hypothesis and suggest that acquirer advisers try to ensure closing by offering a higher price, negatively affecting acquirer returns. This can be interpreted either as a conflict of interest inherent in M&A mandates, or as acquirers having a preference for successful deal execution, rather than for direct merger gains. We also test the deal completion hypothesis directly, however, we do not find evidence nor confutation for top tier banks being more successful at closing deals than other advisers.

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"My code doesn't work and I have no idea why.
My code works and I have no idea why."

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1 Introduction

Top tier banks are viewed as the elite of financial advisers and are associated with superior skills and service, demonstrated by large market shares and above-average fee levels. In 2016, the top 10 investment banks[1] advised on 868 M&A deals with a total disclosed value of EUR 1,537 billion, representing 59% of the global M&A advisory market. According to Golubov et al. (2012), top banks charge, on average, a 0.25pp higher M&A advisory fee in public deals, than other advisers. While some view the higher fees as a premium paid for better quality, others debate the actual value top banks add to their clients, at the same time also questioning the motives that drive them.

Attention around this topic first increased in the late 1980s when criticism grew over the excessive merger fees charged by investment banks. As a response, McLaughlin (1990) published his article, concluding that the press, which was one of the major sources of that criticism, overstated the level of M&A compensations by including underwriting and other types of fees in their calculations. McLaughlin's findings nonetheless did not allow for a conclusion on whether the fees charged are excessive, but his research did shed light on another interesting aspect of the topic. Under common advisory contracts, a large part of the advisory fee is contingent on deal completion, generating conflict of interest between advisers and bidders. Buy side advisers have an incentive to increase the offer, as a higher price will more likely result in a successful bid and thus a higher fee, while shareholders want to minimize the price paid, to ensure that larger M&A wealth gains accrue to them.

McLaughlin's paper opened the way to a diverse discussion on the topic, generating a series of studies aiming to analyze and explain advisers' impact on deal performance, as well as the conflict of interest inherent in adviser - client relationships. However, findings and interpretations are dispersed among authors and different papers often arrive at contradicting conclusions. Furthermore, while the US market has been analyzed extensively, scarce research was performed on the European market. While this is understandable given that most top investment banks are based in the US, European M&A market should not be neglected: deals, involving a Europe-based company on either side of

[1] Figures are based on the 2016 global league table downloaded from Bureau van Dijk's Zephyr database. Deals involving multiple top advisers are counted only once. Top 10 banks include (in the order of aggregate deal value): Morgan Stanley, JP Morgan, Bank of America, Goldman Sachs, Barclays, Credit Suisse, Citigroup, Lazard, Perella Weinberg and Deutsche Bank.

the transaction, gave 38% of global deal value and 49% of global deal volume in 2016. To the best of our knowledge, as of the date of this paper, there is no comprehensive, widely published study, that analyzes the relation between adviser reputation and deal performance in European M&A settings. To fill in this research gap, we revisit the questions raised by existing US studies through analyzing deal activity of 15 European countries during the period between 2001 and 2016.

The rest of the paper is structured as follows. Section 2 discusses the theory developed by existing research and presents the contradicting empirical evidence documented in relevant literature. Section 3 examines the differences between the US and European M&A markets and formulates the hypotheses tested in this paper. Section 4 and 5 detail the data collection processes and summarize the research methodology. Section 6 presents and discusses our findings, followed by a brief overview of robustness tests in Section 7. Finally, Section 8 concludes the paper and outlines potential directions for future research.

2 Adviser reputation and deal performance

While standpoints on the topic are conflicting, and results on the relation of adviser reputation and deal performance have so far been ambiguous, existing studies can be organized around a line of dominating hypotheses. In this section, we first present the main hypotheses developed in relevant literature, then review how empirical research on the topic evolved over time, as well as present the conflicting evidence found in these papers.

2.1 The better merger and the skilled negotiation hypotheses

One set of hypotheses poses that clients who hire more reputable advisers realize, on average, higher M&A wealth gains than clients who do not hire top-tier advisers. These hypotheses rely on the notion that top-tier advisers' higher fee compensation and market share reflect exceptional skills and superior client service compared to their counterparts. Based on Bowers & Miller (1990) and Kale et al. (2003), the M&A wealth gain accruing to a client is determined by two main components: the combined wealth gain realized by the negotiating parties (*better merger hypothesis*) and the proportional split of the combined wealth gain between the parties (*skilled negotiation hypothesis*).

The *better merger hypothesis* poses that top-tier advisers are better at identifying and structuring value-creating deals thus generating larger total synergies. This hypothesis therefore predicts a positive relationship between the combined wealth gain realized together by the target and acquirer, and the absolute reputation of both the acquirer and target advisers.

The *skilled negotiation hypothesis* poses that top-tier advisers prevail during merger negotiations and thus their clients receive a larger share of total synergies, on average. This assumption, however, holds only when one party hires a more reputable adviser than the one appointed by the opposite side. For example, if both the acquirer and target hire a top-tier adviser, it is expected that the bargaining power of the parties will even out and additional value will not be shifted to either side. This hypothesis therefore predicts a positive relationship between the client's share of the combined wealth gain and the reputation of the client's adviser relative to the other side's adviser.

These hypotheses suggest that, despite advisory fees being largely contingent on deal completion, market mechanisms punish inferior client performance and thus limit opportunistic behavior of advisers, maintaining the positive relationship between adviser reputation and deal performance.

2.2 The deal completion hypothesis

Rau's (2000) *deal completion hypothesis* predicts that, on average, top-tier advisers complete a larger proportion of the deals they advise on than do non-top-tier advisers, irrespective of the deal performance. The hypothesis relies on the notion that top-tier advisers are preferred because of their better track record in deal execution. Note, however, that the hypothesis does not imply anything about why deal completion rates might differ across advisers. A higher deal completion rate can result either from an adviser's ability to identify deals that have a higher probability of closing, or from its ability to close a deal once hired.

According to the deal completion hypothesis, top-tier advisers' main focus is closing the deals they advise on, reinforced by the structure of M&A advisory contracts that incentivize deal completion. As a result, client deal performance becomes a secondary objective and a positive relationship between adviser reputation and client wealth gain might not be observable.

2.3 Existing empirical evidence

These two mainline hypotheses have been widely discussed in finance literature, largely triggered by McLaughlin's study published in 1990. **Hunter & Walker (1990)** alleviate some of the concerns about excessive merger fees and the misalignment of bank - client interests. They find a significant positive relationship between fees and merger gains, as well as between fees and the effort of the investment bank (proxied by deal complexity). Based on these findings they conclude that standard merger fee structures appear to provide sufficient incentives for investment banks to act in the interest of their clients, and that higher advisory fees can be justified by higher adviser effort.

Instead of directly examining advisory fees, **Bowers & Miller (1990)** focus on the relationship between bank reputation and deal performance. First-tier banks are classified as those persistently earning top positions on tombstones, namely First Boston, Goldman Sachs, Merrill Lynch, Morgan Stanley and Salomon Brothers. Bowers and Miller were among the first to find empirical support for the better merger hypothesis, documenting that deals in which at least one first-tier bank is hired, on either side, generate significantly higher combined wealth gains for the parties than deals where no first-tier bank is hired. However, they find no support in their analysis for the skilled negotiation hypothesis.

A year later, **Michel et al. (1991)** published their paper examining the individual deal performance of six major investment banks, together with a group of 'other banks' consisting of 30 firms. Using a non-parametric rank test, they find that certain second-tier investment banks persistently deliver better advice to their clients (measured by announcement abnormal returns) than certain top-tier banks. Their results contradict those of Hunter & Walker (1990) and Bowers & Miller (1990) and once again question the validity of higher fees charged by prestigious advisers.

A decade later, in his study **Rau (2000)** contrasts the better merger hypothesis with the deal completion hypothesis. He tests the implications of these hypotheses on banks' reputation, that is, whether a bank's market share, as a proxy for reputation, is dependent on the past performance of its clients or its historical deal completion rate. He finds a significant positive relation between banks' market share and historical deal completion rates but no relation with client performance, supporting the deal completion hypothesis. In addition, his non-parametric rank tests show that first-tier banks complete a significantly higher proportion of tenders (but not mergers) than do non-first-tier banks, while also paying a higher premium. This difference is not explained by completing a higher proportion of value-enhancing deals, proxied as positive abnormal return deals.

All of the early studies are based on rather small samples due to limited data availability, which questions their validity and applicability over the total market. Critiques have subsequently also pointed out that these studies are subject to omitted variable bias, as they attribute the full announcement abnormal return to the advisers' reputation, without controlling for deal characteristic that can affect deal performance.

As a response, **Hunter & Jagtiani (2003)** revisit some of the questions presented in earlier papers, mainly focusing on advisory fee structures. They also control for some deal characteristics that can affect deal performance, such as the number of advisers, hostile deals, and tenders. Their analysis shows a positive relationship between adviser reputation and advisory fees, and they also find evidence for the deal completion hypothesis: hiring Tier 1 advisers increases the likelihood of a deal being closed as well as the speed with which it is closed. Moreover, they find that acquirers hiring Tier 1 banks realize significantly lower post-acquisition gains (measured as the difference between market value of the target at closing and the transaction value at announcement) than other acquirers, contradicting the better merger and skilled negotiation hypotheses.

In another study, published in the same year, **Kale et al. (2003)** find support for both the better merger and skilled negotiation hypotheses. In their analysis, in addition to the acquirer adviser's reputation, they also factor in the target adviser's reputation, arguing that top tier banks' added value manifests when the other party hires a lower tier adviser. Using the relative market share of the bidder and target advisers as an explanatory variable, they find that top tier advisers achieve significantly larger gains for their clients than do other banks. In addition, the results show that hiring a top tier adviser on either side of the deal increases combined wealth gains.

Ismail (2010) introduces additional control variables to decrease omitted variable bias, such as method of payment, relative size, geographic reach of the deal and industry relatedness of the parties. The study finds that combined wealth gain increases if a Tier 1 adviser is hired on either side, supporting the better merger hypothesis. The skilled negotiation hypothesis, however, is only proved for target advisers and the analysis does not identify a significant relation (either positive or negative) between adviser reputation and acquirer gains. An additional insight of the paper is that Tier 1 banks generate significantly lower absolute wealth gains for their clients, however, this effect is driven by a limited number of 'large loss deals'.

Reflecting on ambiguous results of existing literature, **Bao & Edmans (2011)** state that prior papers either do not control adequately for deal characteristics, leading to omitted variable bias, or, on the contrary, they include too many controls, part of which can be (and often are) influenced by advisers, thus introducing over-specification and bad controls in their models. They also debate the legitimacy of league tables as a proxy for adviser quality, previously widely applied in relevant research. Bao & Edmans thus use adviser fixed effects instead of league table rankings, and they also attempt to identify and include only those controls that can be viewed as acquirer specific, thus incorporating proxies for empire building and high-quality clients. They find that adviser fixed effects are significantly different from each other, and that bank performance persists over time; proving that advisers do matter for M&A performance. However, they also find that adviser market shares are not related to past performance, suggesting that clients do not 'chase' returns, either due to failure to learn or certain lock-in effects.

In contrast, **Golubov et al. (2012)** apply the 'traditional' league table approach and find that hiring a top tier bank instead of a non-top-tier bank increases the bidder's cumulative abnormal return (CAR) by 1.01% on average, but only in the 'public deal' subsample. According to their study, the higher CAR stems from identifying deals that generate higher combined wealth gains (better merger hypothesis) and from capturing more of this gain at the bidder's side (skilled negotiation hypothesis), at the same time also completing deals faster. In order to account for the high-quality advice, top-tier banks charge, on average, a 0.25pp higher advisory fee in public deals than non-top-tier banks.

Song et al. (2013) incorporate a recently popular classification of advisers, namely, they examine whether boutique advisers add more value to clients than full-service banks, and if so, under which conditions. According to their study, acquirers are more likely to hire boutiques in complex and hostile deals and they find that deal premium (deal duration) is lower (higher) when hiring boutiques on the acquirer side. In contrast to previous studies, they interpret longer deal duration as spending more time on due diligence, deal structuring and negotiation, thus ensuring quality and delivering higher value to clients. Lower premiums are attributed to M&A focused experience and industry-specific knowledge, that characterize boutique firms and which enhance their negotiation power.

McConnell & Sibilkov (2016) take a new approach and, rather than comparing different groups of advisers, examine whether market mechanisms counteract the conflict of interest inherent in M&A advisory mandates. According to their analysis, advisers with positive deal performance track records have higher chances of being retained for M&A deals. Furthermore, the change in advisers' market share is positively correlated to historical acquisition returns of their clients. This indicates that the market, indeed, has a mechanism that rewards 'better' advisers, and punishes those who prioritize fee maximization over client interests.

A set of studies extends the research area to examining the relation between M&A mandates and other client - bank relationships. **Kolasinski & Kothari (2008)** shed light on analyst conflicts arising from M&A relations: they find that acquirer adviser banks are more likely to upgrade their recommendations around M&A deals than non-adviser banks, and target advisers are also more likely to upgrade acquirer recommendations in all-stock deals, after the exchange ratio is set. **Sibilkov et al. (2013)** document that bidders are more likely to choose a bank as an M&A adviser if they have provided equity research on the company, and, in turn, these chosen banks are less likely to terminate and more likely to initiate coverage for the given firm, following the M&A mandate. **Forte et al. (2010)** find that targets, when hiring an adviser, are more likely to use their main bank with whom they have prior relationship, and that this prior relationship significantly increases wealth gains. They argue that information acquired by the advisers during previous engagements can be used to certify the quality of transaction.

Other complementary papers analyze the role of individual skills. **Ertugrul & Krishnan (2011)** look at individual influence of investment bankers, rather than banks, arguing that banks' performance stem from top bankers connections and knowledge. According to their study, investment banker fixed effects are significant for different measures of deal performance (CAR, long-term abnormal ROA and BHR and completion time), even after controlling for bank fixed effects. **Jaffe et al. (2013)**, instead, examine the role of CEOs' skills in M&A, and conclude that CEOs with successful track record in acquisitions earn, on average, 1.02% higher returns on their next deal than CEOs who have negative track record.

3 Research motivation

3.1 The European M&A market

Most research conducted on M&A activity is focused on the US market. This holds true, in particular, for studies investigating the relationship between adviser reputation and deal performance. To our knowledge, no comprehensive, widely published paper exists at the present, that examines the European M&A market - a research gap this paper aims to fill. The scarcity of Europe focused research can lead to deriving conclusions about the European M&A market based on US findings. The existence of a number of important differences between the two M&A markets, however, makes such inferences problematic and a separate research on the European market worth wile.

One reason for the scarcity of Europe-focused studies on the topic is the weaker historical presence of M&A activity in the region. Except for the UK, Europe did not take part in the merger waves that took place in the US before the 60's, and experienced an uptick only gradually, following the increased interdependence of the European economies, which triggered industry consolidation (Vancea 2013). Although since then, merger waves have been more aligned between the US and Europe, and Europe has also seen a convergence of national markets, the two regions remain structurally different.

The difference in take-over history appears to be correlated with the competitiveness of the respective markets. Alexandridis et al. (2010) investigate a worldwide M&A sample over the time period between 1990 and 2007, and find the US to be the most competitive market, measured by the percentage of listed firms being acquired in each year. When analysing announcement returns in more detail, they find M&A market competitiveness to have a significant influence on acquirer and target cumulative abnormal returns (CAR) at transaction announcement. In the US, acquirers experience, on average, a significant negative announcement CAR, whereas targets experience large positive CARs. Other world regions, including most European countries, tend to see a more even split of merger gains, with significant positive gains accruing to both acquirers and targets, and targets thus experiencing lower CARs than in the US. Besides deal specific characteristics, Alexandridis et al. (2010) relate announcement return deviations to a number of structural differences displayed by the regions, that reach beyond the level of market competition. When controlling for these characteristics, however, the significant impact of competitiveness still persists.

Among structural characteristics of take-over markets, differences in legal systems are some of the most prominent factors. Rossi & Volpin (2004) find a positive relationship between investor protection in a given country and premia paid. US regulations are more shareholder focused, offering stronger investor protection than most countries in Europe. Alexandridis et al. (2010) also find support for this effect in their worldwide sample. As higher institutional ownership can potentially imply better acquisition decisions, the level of institutional ownership is another factor that can lead to different results observed across countries (Chen et al. 2007). The Ferreira & Matos (2008) institutional ownership index shows highest levels for the US and Canada. The relationship between acquirer CAR and institutional ownership, however, remains insignificant in Alexandridis et al.'s (2010) analysis, when controlling for competitiveness and other country specific factors. They also investigate the impact of corporate governance differences between the countries, and find the average percentage of independent directors within a country to have a significant influence on acquisition returns.

The above mentioned factors differ between the US and most European countries. Even though these factors could theoretically be controlled for, M&A studies regularly only examine domestic US transaction, making these country specific variables irrelevant. Alexandridis et al. (2010) also only investigate domestic transactions, thereby potentially overlooking other factors. Last but not least, hostile take-over attempts being less common and national interest still being higher in some industries within Europe, further point towards differing deal dynamics between the two regions.

3.2 Hypotheses formulation

Existing research on the topic can be organized into two main groups based on their approach to hypothesis testing. One set of papers examine which performance measures (value gains or completion rates) drive advisers' market share and thus draw conclusions on how advisers add value to their clients. The second group of studies examine the factors that can potentially add value to clients and directly test how these factors are related to adviser reputation.

The market-share approach assumes that clients are able to recognize and measure the value they receive from investment banks, and they 'follow value', that is, they will hire advisers that add more value to their clients, be it higher returns or better completion rates. However, there are multiple reasons that this assumption might not hold empirically. On one hand, clients might not be able to directly recognize and measure advisers' value due to information asymmetry, and thus they rely on media publications, public opinion and league tables when choosing their advisers, resulting in a 'lock-in' effect. Indeed, the persistence observed in market shares and rankings is one of the main reasons why most studies use league tables as a proxy for adviser reputation. Furthermore, the choice of advisers is also affected by existing relationships between clients and banks, as pointed out by Forte et al. (2010) and Sibilkov et al. (2013). These dynamics together complicate the analysis of the relationship between adviser reputation and value generated for clients.

Given the limitations of the market-share approach, we will follow the direct-measure approach, also because we believe it provides more practical insights and more direct implications for economic interpretation. Nevertheless, we acknowledge the advantages of the market-approach and consider it as an interesting topic for future research.

Based on relevant literature and empirical evidence, we will test the following hypotheses.

3.2.1 Adviser reputation and client wealth gain

Empirical evidence shows that more reputable advisers charge higher advisory fees, in general, signalling superior skills and client service. One way to provide higher value for clients is through ensuring larger merger wealth gains accrue to them. We test this proposition by examining the relationship between adviser reputation and acquirer, as well as target announcement abnormal returns, and expect to find a positive relation.

> ***H 1a.*** *Acquirers (targets) hiring at least one Tier 1 adviser realize higher announcement abnormal returns than acquirers (targets) who do not hire Tier 1 advisers.*

In addition, based on Kale et al. (2003), announcement returns should also be affected by the reputation of the adviser hired by the other party, and we expect this relation to be negative.

H 1b. *Acquirers (targets) realize lower announcement abnormal returns if the target (acquirer) hires at least one Tier 1 adviser.*

Apart from examining the 'pure' effect of hiring top tier advisers on either side, we are also interested in the potential amplification / suppression effects that may arise when top tier advisers are appointed on both sides. On one hand, as an extension to the better merger hypothesis, one can suppose larger combined wealth gains when there are multiple top tier advisers retained on a deal, assuming that Tier 1 advisers work better together and strengthen each others' abilities. At the same time, based on the skilled negotiation hypotheses, it can be presumed that negotiation skills of the advisers even out if Tier 1 advisers are hired on both sides. Together these assumptions predict a positive interaction term between acquirer and target adviser reputation. However, it can also be argued that hiring Tier 1 advisers on both sides adds complexity to the deal process and negotiation, offsetting some of the value creation, resulting in a negative interaction term. Given these opposing effects we do not propose an explicit hypothesis regarding the interacting relation between acquirer and target adviser reputation, nevertheless, we examine the interaction term in our regressions.

Although Hypothesis 1 provides an assumption on the effect of adviser reputation on client wealth gain, it does not have an implication on the source of this wealth gain. The better merger and skilled negotiation hypotheses propose that a client's announcement wealth gain is the function of the combined wealth gain generated through the merger and the client's share of these wealth gains. It is expected that hiring more reputable advisers on either side of the deal increases the combined wealth gain of the parties (better merger hypothesis), and that the proportion of this gain received by a party is positively related to the reputation of its adviser (skilled negotiation hypothesis). Furthermore, this positive relationship will be moderated by the reputation of the other party's adviser. We thus propose the following three hypotheses, and, similar to announcement returns, we examine the effect of both parties hiring top advisers without forming an explicit hypothesis.

H 2. *Deals, where at least one Tier 1 adviser is hired by either party, generate higher combined wealth gains than deals where no Tier 1 adviser is hired.*

H 3a. *Acquirers hiring at least one Tier 1 adviser receive a larger share from the combined wealth gain generated through the merger than acquirers that do not hire Tier 1 advisers.*

H 3b. *Acquirers receive a smaller share from the combined wealth gain if the target hires at least one Tier 1 adviser.*

In addition to the above hypotheses, we will also look at an alternative measure of target wealth gain. Following from the propositions above, we expect deal premium to show a positive relationship with target adviser reputation, and a negative relationship with acquirer adviser reputation.

H 4a. *Targets hiring at least one Tier 1 adviser receive a higher acquisition premium than targets who do not hire a Tier 1 adviser.*

H 4b. *Targets receive a lower acquisition premium if the acquirer hires at least one Tier 1 adviser.*

3.2.2 Adviser reputation and deal completion

We will also test the implications of the deal completion hypothesis. We expect to find a positive relation between adviser reputation and the probability of the deal being completed, if the deal completion hypothesis holds.

H 5. *Deals, where at least one Tier 1 adviser is hired by either party, are more likely to be completed than deals where no Tier 1 adviser is hired.*

4 Data

4.1 Deal and return data

4.1.1 Data collection

As a first step, we retrieve an initial list of mergers and acquisitions from Bureau van Dijk's Zephyr database, comprising of minority-to-majority transactions announced between 1 January 2001 and 31 December 2016. Given that we intend to analyse announcement returns, we limit the search scope to deals where either the target or the acquirer is a currently or previously listed entity. (Zephyr did not have the option to filter based on listing status at announcement date.) We further narrow down our screening to deals where both parties are located within Europe (within one of the 15 countries that are included in the MSCI Europe Index, see Table 1), the deal value exceeds EUR 1 million, and, in accordance with Kale et al. (2003), the acquisition represents an at least 15% ownership.

Table 1: Deal data screening criteria

We used the Zephyr database to retrieve data on European M&A transactions announced between 1 January 2001 and 31 December 2016. Only minority-to-majority transactions are included, with an acquired stake of at least 15% and a deal value of at least EUR 1 million. The list of countries were eventually restricted to the countries included in the MSCI Europe Index. Only those deals are included where either the acquirer or the target, or both, are currently listed or were listed at the time of the transaction. (Zephyr did not allow to filter based on announcement date listing status.)

Category	Screening criterion
Deal type	Merger or Acquisition
Announcement date	01/01/2001 - 31/12/2016
Percentage of stake	Initial stake < 50 % or unknown minority Final stake > 50 % or unknown majority Acquired stake > 15%
World region	Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom (Target and Acquirer)
Deal value	> EUR 1 million
Listing status	Target or Acquirer listed or delisted

For the further analysis, we split the total sample into acquirer and target datasets. Transactions involving multiple acquirers / targets (listed or unlisted) are dropped from the respective datasets. Thus, deals including multiple acquirers are dropped from the acquirer dataset, but not form the target dataset, and vice versa. We do so since, in cases where at least one of the multiple targets / acquirers are not listed, the full announcement effect cannot be captured adequately, and Zephyr does not provide a split of deal value among the involved parties. We include both completed and non-completed deals in our analysis.

The initial M&A dataset thus comprises of 2,632 deals with listed targets, and 11,680 deals with listed acquirers. Based on this, we compile an ISIN list of the companies and collect stock and market data from Thompson Reuters Datastream. As Zephyr does not allow for filtering targets / acquirers based on announcement date listing status, we include all listed and delisted companies in the Datastream request and further filtering is based on the availability of stock return data around the announcement date.

Due to the quality and rounding issues of Datastream's automatically calculated Return Index (RI), reported by Ince & Porter (2006), we calculate total return index manually by downloading stock split adjusted price and dividend data from Datastream, using the following formula, analogous to Datastream's RI:

$$\begin{aligned} RI_t &= RI_{t-1} * \tfrac{P_t}{P_{t-1}} \qquad \text{if } t \neq \text{ex-dividend date} \\ RI_t &= RI_{t-1} * \tfrac{P_t + D_t}{P_{t-1}} \qquad \text{if } t = \text{ex-dividend date} \end{aligned} \tag{1}$$

Following the Datastream request, stock data availability decreases the samples to 2,417 deals for the listed target dataset and 10,131 deals for the listed acquirer dataset.

Bartholdy et al. (2007) report potential bias in an event study setting for stocks that are not thickly traded. To control for this bias they suggest separating stocks according to their trading frequency, and define stocks to be thickly traded if they show trading activity on more than 80% of trading days in the estimation window. Following this approach, we drop non-thickly traded stocks from our sample.

Furthermore, in line with common event study practices, we also drop stocks from the sample if trading activity is not observed on each day of the event window. Bartholdy et al. (2007) point out, that stocks affected by a given event have higher probability of trading around the event date, as compared to other stocks which are also experiencing the event, but are unaffected by it. Consequently unaffected stocks are more likely to be dropped from the sample, biasing the analysis towards finding a more significant effect. We acknowledge this potential bias, given that the sample only includes thickly traded stock, the impact can however be expected to be negligible. Imposing these trading activity restrictions further decreases the data set to 1,219 deals for the listed target sample and 6,994 deals for the listed acquirer sample.

We also remove 'penny stocks' from our sample, defined as stocks having an average price below 1 currency unit during the full period of the estimation and event windows. We do so as these stocks do not show normal price reaction, given the price quotation limitations. For example, we remove a UK (German) stock if it has an average price of GBP 0.1 (EUR 0.1), since the smallest possible price reaction for this stock is GBP 0.01 (EUR 0.01) on average, representing a 10% change. Removing penny stocks further decreases the target sample to 976 deals and the acquirer sample to 6,155 deals.

To ensure that only common stocks are included in the analysis, we download information on issue types from both Datastream and Compustat. As neither series is complete, we introduce the following hierarchy of the stock classification series: Datastream > World Scope (via Datastream) > Compustat. We exclude all ISINs that represent non-common stocks or for which the stock type can not be determined. This reduces the sample to 546 deals involving listed targets and to 4,249 deals involving listed acquirers.

In the acquirer sample, we introduce the additional condition that the value of the acquired stake (proxied by deal value) must represent at least 10% of the market value of the acquirer, in order to ensure a measurable stock price reaction upon announcement. We also lose some observations due to the availability of control variables data, downloaded from Zephyr and Datastream. Finally, we winsorize our sample at 1%, based on the main dependent variables (CAR and deal premium). Thus our final sample includes 407 deals in the target and 1,037 deals in the acquirer sample.

4.1.2 Descriptive statistics

Table 2 presents the distribution of advisers for the final acquirer and target M&A samples. In the listed acquirer sample, 645 acquirers and 359 targets retain an adviser on the deal, while in the listed target sample 349 acquirers and 345 targets hire one. We thus observe a higher density of advisers in the target sample as compared to the acquirer sample. The target sample only includes listed targets, resulting in an average (median) deal value of EUR 4,410 (646) million compared to the EUR 1,807 (143) million observed in the acquirer sample. As larger deal size adds complexity and also increases the economic importance of the deal, it follows naturally that both acquirers and targets are more likely to hire advisers. In the acquirer sample, however, even though we introduced the 10% relative size criteria, targets (and consequently deal value) is smaller on average, decreasing the probability of an adviser being hired on the deal. (Note that, as described in Section 4.1.1, both samples are restricted to transactions having a deal value of at least EUR 1 million.)

Table 2: Adviser distribution within the target and acquirer samples

This table presents the distribution of advisers across and within the samples, after filtering for all criteria described in Section 4.1.1. We observe higher density of advisers in the target sample, where the ratio of acquirer advisers to target advisers is also more even. We attribute this to the fact that the target sample includes only listed targets, resulting in higher average deal value and complexity, increasing the likelihood of the parties hiring an adviser.

	Number of deals	
	Acquirer sample	Target sample
Full sample	1,037	407
At least one acquirer adviser is hired	645	349
At least one target adviser is hired	359	345
Average deal value in EURm	1,807	4,410
Median deal value in EURm	143	646

4.2 Adviser and league table data

4.2.1 Data collection

To collect adviser data, we retrieve information from the Zephyr database on mergers and acquisitions announced between January 2001 and December 2016. Rau (2000) argues that advisers capably representing their clients' interests will have a larger market share among announced deals as they might withdraw from disadvantageous deals, decreasing their share within completed deals. This gives rise to use announced deals when compiling league data, rather than completed deals. Similar to the deal data sample, we include only minority-to-majority transactions with an acquired stake of at least 15% and a deal value of at least EUR 1 million. The sample is further restricted to deals where both parties are based in one of the 15 countries included in the MSCI Europe Index.

In the raw sample as downloaded from Zephyr, the same adviser is often presented under different names (for example, UBS is listed under the names UBS and UBS AG) or under the name of their subsidiaries (for example UBS Warburg is listed separately although it is a subsidiary of UBS). To adjust for this, we perform manual checks where we reconcile adviser names to a common name of the parent (following the earlier example, all UBS companies in the adviser list were adjusted to 'UBS' in our data). We argue that although a given bank might sometime legally provide its services through a subsidiary, the adviser reputation perceived by the client is the same as if services were legally provided by the parent itself. This is further supported by the fact that most banks have a main European office (usually based in London) that is involved in M&A mandates within the whole geographic area. After the name reconciliation, we also filter out multiple listings of an adviser under the same deal to avoid double counting.

We further adjust for the merger of Bank of America and Merrill Lynch. Before the merger of the two companies, Bank of America had very limited presence in the European M&A advisory market (only 9 deals over the course of 5 years in our data). However, deals advised by Merrill Lynch are listed under Bank of America starting from 2009 (when the Bank of America - Merrill Lynch transaction was closed), dramatically increasing BoA's share in Europe. This naming convention would falsely categorize Bank of America as a top-tier adviser over the full observation period, potentially distorting our analysis and results. To correct for this, we list all deals advised by either of the two firms during or after 2009 under the name 'BAML' (Bank of America Merrill Lynch). During our manual check, we did not identify any other occurrences where Zephyr's naming convention would pose a similar problem.

As a result of these adjustments, our final sample includes a list of 343 unique advisers.

5 Methodology

5.1 Adviser reputation

5.1.1 Measuring adviser reputation

Following the most common approach in relevant literature, we use market share as a proxy for adviser reputation, converted into a binary dummy variable (Tier 1 or non-Tier 1). While some studies use market share as a continuous measure (for example Kale et al. (2003)), Fang (2005) states that a binary variable (a dummy) is preferable when proxying for adviser reputation. On the one hand, from an economic perspective, the binary variable reflects the two-tier classification of Wall Street, where banks are either categorized as a bulge bracket or not. From an econometric perspective, applying a binary variable in the regression is more adequate than using a continuous measure (i.e. using deal values or rankings as it is), as the use of a continuous variable inherently assumes that it measures reputation precisely and that it has a constant effect on the dependent variable(s).

5.1.2 League table

In line with Rau (2000), we first compile annual league tables for each year of our observation period. The league tables are based on deal value and each adviser is given full credit for every deal they advise on. Since we intend to examine the value created for both acquirers and targets, in contrast with Rau (2000), we consider both sell and buy side mandates when assembling the league tables.

Based on the annual league tables we compile an overall league table for the full period, sorted based on the average annual ranking of the advisers. For advisers that were inactive (i.e. advised on no announced deals in the sample) in a given year, Rau assigned the lowest ranking. For example, if there are 100 active advisers in a year, all advisers that have no announced deals in the given year are assigned the ranking 101. In contrast, we consider only the active years for each adviser when examining persistence and calculating average ranking. Assigning the lowest ranking for inactive years would falsely categorize Tier 1 advisers as not Tier 1, in case they go bankrupt (for example Lehman Brothers) or are acquired (for example Merrill Lynch). Arguably, these advisers' reputation during the active years was independent and unaffected by subsequent events that led to them becoming inactive. Additionally, to ensure persistence, we exclude advisers from the final league table that were active for less than 3 years out of the total 16 years of the examined period. Table 3 presents the top 30 advisers based on average ranking across years.

5.1.3 Adviser tier classification

Most existing studies categorize advisers based on a two-tier [Forte et al. (2010), Ismail (2010), Golubov et al. (2012)] or three-tier [Rau (2000), Hunter & Jagtiani (2003), Song et al. (2013)] system. We follow a two-tier system as it is in line with the two-tier Wall Street split mentioned by Fang (2005). We also deem it to provide a less arbitrary cut-off than a multi-tier split, as, while first tier usually only includes bulge brackets, a rather homogeneous group, second tier advisers form a diverse group including multi-service banks, big four companies, local banks and boutiques. This suggests that a purely deal value based division of second tier advisers might not be adequate. The top-tier cut-off applied in previous studies varies between top 3 banks (Forte et al. (2010)) and top 15 banks (Hunter & Jagtiani (2003)). For our analysis, we categorize advisers that have an average annual ranking of at least 10 as Tier 1, and all other banks as Tier 2 (non-Tier 1). This leaves us with 12 Tier 1 advisers, namely: Merrill Lynch, Morgan Stanley, BAML, Citigroup, Lazard, JP Morgan, Deutsche Bank, Rothschild, Goldman Sachs, Lehman Brothers, UBS and Credit Suisse.

All Tier 1 banks have been active in all years, except for Lehman Brothers (given their bankruptcy) and Merrill Lynch / BAML (given the merger) and are also highly ranked based on the overall deal value during the full period. Tier 1 advisers, in general, have a higher average deal value and usually advise on more deals per year than Tier 2 advisers. Apart from the two prestigious 'boutique' banks Lazard and Rothschild, all Tier 1 advisers belong to the group of 'bulge bracket' banks according to the common classification.

Our Tier 1 group largely overlaps with the top-tier categories presented in other papers, however, some differences can be observed. Given that we focus our analysis on the European M&A advisory market, some banks are included in our Tier 1 group that are not presented in existing papers restricted to the US market, such as UBS and Deutsche Bank. Another difference is the time period observed: while we analyze the period between 2001 and 2016, most prior papers examine earlier years, thus they include

Table 3: European M&A league table - Top 30 advisers

The table presents summary information on the deal activity of the top 30 advisers out of a total unique advisers of 343. The league table is based on data on M&A transactions announced between 1 January 2001 and 31 December 2016, as downloaded from the Zephyr database. Only minority-to-majority transactions are included, with an acquired stake of at least 15% and a deal value of at least EUR 1 million. Data includes both sell and buy side mandates and each adviser is awarded full credit for each deal they advise on. Advisers are ranked by 'Average rank', calculated as the average of annual, deal value based rankings in active years during the observation period. Only advisers with at least 3 active years are included. Advisers having an average ranking of at least 10 are categorized as Tier 1, all other banks are included in Tier 2. In our sample, Tier 1 advisers together account for 68% (26%) of total deal value (deal volume), while the top 30 advisers together account for 89% (48%).

	Adviser	Active years	Avg. rank	Overall rank	Total deals	Total deal value (mEUR)	Avg. deals per year	Avg. deal value (mEUR)
Tier 1								
1	Merrill Lynch	8	3	7	163	1,156,560	20	7,095
2	Morgan Stanley	16	4	1	319	1,609,023	20	5,044
3	BAML	8	6	15	92	563,155	12	6,121
4	Citigroup	16	7	3	284	1,448,818	18	5,101
5	Lazard	16	7	8	406	1,142,381	25	2,814
6	JP Morgan	16	8	2	325	1,532,525	20	4,715
7	Deutsche Bank	16	8	5	268	1,252,807	17	4,675
8	Rothschild	16	8	6	529	1,160,597	33	2,194
9	Goldman Sachs	16	8	4	186	1,333,869	12	7,171
10	Lehman Brothers	8	9	12	118	854,948	15	7,245
11	UBS	16	9	9	311	1,058,612	19	3,404
12	Credit Suisse	16	10	11	241	949,729	15	3,941
Tier 2								
13	BNP Paribas	16	13	10	232	1,054,367	14	4,545
14	HSBC	16	16	13	137	666,133	9	4,862
15	Societe Generale	16	25	18	95	253,242	6	2,666
16	KPMG	16	26	22	436	143,625	27	329
17	Dresdner Kleinwort	9	27	19	124	238,694	14	1,925
18	Perella Weinberg	8	27	21	20	145,373	2	7,269
19	Greenhill	12	28	20	47	210,004	4	4,468
20	SEB	16	28	30	169	81,566	11	483
21	ABN Amro	13	30	14	218	564,667	17	2,590
22	Credit Agricole	14	30	24	54	131,959	4	2,444
23	Ernst & Young	16	31	17	250	328,709	16	1,315
24	PwC	16	31	32	353	73,724	22	209
25	Ondra LLP	3	31	49	9	25,116	3	2,791
26	Centerview	3	35	69	4	11,415	1	2,854
27	UniCredit	13	36	34	57	70,795	4	1,242
28	Mediobanca	15	37	26	60	121,091	4	2,018
29	Nordea	16	37	43	84	33,996	5	405
30	Deloitte	16	38	27	287	111,663	18	389

advisers that have since been dissolved / acquired (for example Salomon Smith Barney).

5.1.4 Adviser reputation dummies

Based on the adviser tier classification, we assigned two dummy variables to each deal (TIER1_a and TIER1_t) that take the value of 1 if the acquirer (TIER1_a) or target (TIER1_t) hires at least one Tier 1 adviser, respectively. Using these dummies, we can distinguish four mutually exclusive combinations of acquirer - target advisers: (1) neither the acquirer nor the target hires a Tier 1 bank, (2) only the acquirer hires a Tier 1 bank, (3) only the target hires a Tier 1 bank, (4) both the acquirer and target hire a Tier 1 bank. In our analysis, we applied combination (1) as the base case, and incorporated the two dummy variables as proxies for combinations (2) and (3), hereinafter referred to as 'adviser dummies'. These adviser dummies form the main explanatory variables in our analysis. Combination (4) is captured through interacting TIER1_a and TIER1_t, where the interaction term can be interpreted as the amplifying / offsetting effect between Tier 1 advisers. The total effect of adviser reputation in combination (4) can be computed by adding up the coefficients of TIER1_a, TIER1_t and the interaction term. Figure 1 summarizes the four combinations and the relevant dummies.

Figure 1: Summary of adviser reputation dummies

	Acquirer does not hire a Tier 1 adviser	**Acquirer hires a Tier 1 adviser**
Target does not hire a Tier 1 adviser	*Combination (1)* -	*Combination (2)* TIER1_a
Target hires a Tier 1 adviser	*Combination (3)* TIER1_t	*Combination (4)* TIER1_a * TIER1_t

This approach is in line with Fang's (2005) proposition that econometrically a binary variable is more adequate when proxying for adviser reputation, and at the same time, it also captures the relative reputation of the acquirer and target advisers, emphasized by Kale et al. (2003). In theory, it could happen that the acquirer hires a Tier 1 bank while the target hires an adviser with a relatively low ranking, say 50. In such cases, a continuous or quasi-continuous variable might better capture the differences in adviser reputation. However, it is reasonable to assume that adviser choice of the target is related to the adviser choice of the acquirer thus we deem the binary variables adequate for our analysis. (For example, if the acquirer hires a Tier 1 adviser it is most likely that the target will hire an adviser whose reputation is relatively close to the acquirer's adviser's.)

5.2 Announcement abnormal returns

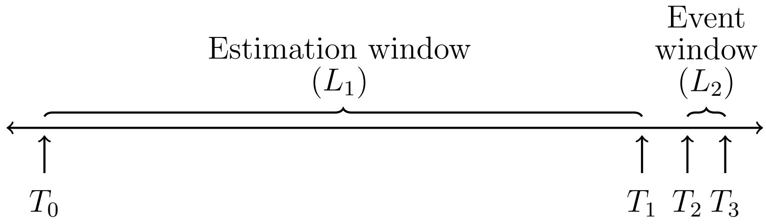
In line with existing studies, we measure the value gain generated through M&A transactions by examining announcement abnormal returns, computed based on event study methodology. We thus download information on announcement date for each transaction from the Zephyr database. If the announcement date is not a trading day the event date is moved to the next trading day after the announcement date.

The event window spans a number of days around the event date, in order to observe most of the announcement effect, given the fact there is some uncertainty associated with the actual announcement date (e.g. announcing the transaction during or after trading hours or information leakage). Event windows used in previous literature on the topic usually span to 3 trading days ([t-1:t+1], as in Bao & Edmans (2011), Ertugrul & Krishnan (2011)) or 5 trading days ([t-2:t+2], as in (McConnell & Sibilkov (2016), Golubov et al. (2012), Ismail (2010)). We set the event window to [t-2:t+2], however, in Section 7, we perform sensitivity tests by varying the length of the event window.

The estimation window is defined as a period of time before the event date in which the stock price is assumed to be unaffected by the information about the planned transaction. Estimation windows are usually set to reflect approximately a year of trading activity, i.e. 200 to 250 trading days (Bartholdy et al. 2007). We set the estimation window to end 10 trading days before the event date, in order to avoid the stock price being affected by information leaks around the announcement date. The start date is set at t-260 trading days, resulting in the estimation window to span from t-260 to t-11. Similar to the event window, we also perform robustness tests on the length of the estimation window.

We base our return estimations on a Total Return Index (TRI), calculated manually for each stock based on Datastream's 'Price' and 'Dividend' datapoints. Even though imposing the thickly traded condition lightens some concerns regarding estimation bias, missing values in the estimation window still pose a challenge when estimating the market model used for calculating abnormal returns. The two most common methods to address

Figure 2: Event study timeline



T_0	=	−260	Beginnig of estimation window
T_1	=	−11	End of estimation window
T_2	=	−2	Beginnig of event window
T_3	=	2	End of event window
L_1	=	250	Length of estimation window
L_2	=	5	Length of event window

this issue are the trade-to-trade return approach and the lumped return approach. Under the trade-to-trade method, days without trading activity are omitted from the sample and the benchmark index is compounded accordingly. Under the lumped return method, days without trading activity are kept in the sample at the latest closing price, thus they are treated as zero return days. Campbell et al. (2010) report that trade-to-trade returns perform better in event study settings than do lumped returns, therefore, we use trade-to-trade returns in our analysis.

We calculate trade-to-trade returns in line with the methodology outlined by Maynes & Rumsey (1993) with the observed multiperiod return (n_t denotes the return interval length) ending on day t equalling:

$$R_{j,n_t} = ln\left[\frac{P_{j,t}}{P_{j,t-n_t}}\right] = ln\left[\frac{P_{j,t}}{P_{j,t-1}} \times \frac{P_{j,t-1}}{P_{j,t-2}} \times ... \times \frac{P_{j,t-n_t+1}}{P_{j,t-n_t}}\right] \tag{2}$$

The use of log returns allows for R_{j,n_t} to be the sum of n_t unobserved one day returns for stock j, while R_{m,n_t} constitutes the market index return for the corresponding period. The single-factor market model accordingly is:

$$R_{j,n_t} = \alpha_j n_t + \beta_j R_{m,n_t} + \sum_{s-0}^{n_t-1} \varepsilon_{j,t-s} \tag{3}$$

To correct for heteroskedasticity introduced by the aggregation of the error terms (variance of the error terms equals $n_t\sigma_j^2$), the return data is divided by the square root of

n_t. Accordingly abnormal returns are calculated as follows:

$$AR_{j,n_t} = R_{j,n_t} - E[R_{j,n_t}] = R_{j,n_t} - \hat{\alpha}_j n_t - \hat{\beta}_j R_{m,n_t} \tag{4}$$

Both samples, target and acquirer, include some observations with rather low trading volume where the price is not affected by the trade and thus the trading day becomes a zero return day, despite the trading activity. We omit these days from the sample and treat them analogous to trading days on which no trade has happened. However, the trading days omitted this way are not considered as no trading activity days when classifying stocks as thickly and non-thickly traded. Table 4 presents descriptive statistics of the trade-to-trade return data of listed acquirers and targets included in the respective M&A samples. The data is presented separately for the estimation and event window used in the calculation of announcement returns.

Table 4: Return characteristics

This table presents descriptive statistics for the return data of listed acquirers and targets included in the respective M&A samples. The data is presented separately for the estimation and event window used in the calculation of announcement returns (see Section 5.2). Days on which trades occurred but which nonetheless were zero return days were dropped from the sample. This was not considered for the classification of stocks as *thickly traded* and explains the relatively low average number of return days in the estimation window (250 trading days), when compared to the 80% days with trading activity threshold for thickly traded stocks.

	Acquirer sample		Target sample	
Trade-to-trade returns	Estimation window	Event window	Estimation window	Event window
Average	0.0006	0.0049	0.0005	0.0221
Median	0.0002	0.0028	−0.0002	0.0037
Standard deviation	0.0315	0.0463	0.0314	0.0868
Skewness	9.4144	2.2121	2.9834	2.2633
Kurtosis	1,462.4130	65.5912	176.6762	57.2532
Avg. non-zero-return days	216.7155	5.0000	216.1242	5.0000

Abnormal returns are compounded over the event window [t-2:t+2] to calculate cumulative abnormal return (CAR) for each transaction. To correct for outliers, CARs are winsorized at 1/99%. Table A.1 and A.2 show information on average CAR per year and country, based on the winsorized sample. Furthermore CAR is tested in each of the two samples, using two non-parametric and one parametric tests, which are according to Campbell et al. (2010) well specified for multi-country event study settings using trade-to-trade returns. CAR is found to be significantly different from zero in all three tests. The test statistics are reported in Table 5, details for the calculation can be found in the Appendix.

Table 5: CAR characteristics and test statistics

This table presents statistics on CAR characteristics for the acquirer and target sample. The presented statistics are based on pre-winsorization samples. Given the large outliers in both samples we decided to use a 1%/99% winsorized sample for the further analysis. The same statistics for the winsorized samples are presented in Table A.6. The calculated CAR's of both samples are statistically significantly different from zero at the 1% level, based on all three tests performed. Details on the calcualtion of the test statistics can be found in Section A.1.

	Test statistic	Acquirer sample	Target sample
Average CAR		0.0220	0.1140
Median CAR		0.0151	0.0755
Minimum CAR		−0.8338	−1.4783
Maximum CAR		0.9903	1.3855
0.01 Percentile		−0.2018	−0.1136
0.99 Percentile		0.2865	0.7143
Standard deviation CAR		0.0983	0.1838
Standardized cross sectional test	Z	7.6618***	12.6759***
Generalized sign test	Z	8.4735***	12.8313***
Rank test	t	6.5676***	8.4208***
Observations		1,058	420

*p<0.1; **p<0.05; ***p<0.01

5.3 Combined wealth gain

Following Kale et al. (2003), we measure combined wealth gain (CWG) as the sum of the wealth gains realized by the acquirer and target. Acquirer wealth gain (AWG) is calculated as the product of the announcement abnormal return of the acquirer and the acquirer's market capitalization 20 trading days prior to announcement. We use the market cap as of the 20 trading days prior to the announcement date to mitigate the effect of information leakage. Target wealth gain (TWG) is calculated in a similar way but is adjusted for the toehold ownership of the acquirer. Combined wealth gain is denominated in thousands of euro and is converted from local currency to euro using the spot exchange rate as of the respective date (t-20 days) for each stock, as provided by Datastream.

$$\begin{aligned} CWG = & \underbrace{CAR^{Acquirer}_{[-2,+2]} \times Marketcap^{Acquirer}_{[-20]}}_{\text{AWG}} \\ & + \underbrace{CAR^{Target}_{[-2,+2]} \times Marketcap^{Target}_{[-20]} \times (1 - Toehold)}_{\text{TWG}} \end{aligned} \tag{5}$$

Following Kale et al. (2003), we calculate the acquirers share of the combined wealth gain (ASOCWG) as the fraction of the acquirers wealth gain and the combined wealth gain, if the combined wealth gain is positive, and as one minus this ratio, if the combined wealth gain is negative.

$$ASOCWG = \begin{cases} \frac{AWG}{CWG}, & CWG \geqslant 0 \\ 1 - \frac{AWG}{CWG}, & CWG < 0 \end{cases} \tag{6}$$

5.4 Deal premia

To calculate deal premium (PREMIUM), we obtain data on offer price for each deal from the Zephyr database. We compute deal premia as the ratio of offer price to target share price 20 trading days prior to announcement, minus one.

$$PREMIUM = \frac{Offerprice}{Shareprice^{Target}_{[-20]}} - 1 \tag{7}$$

5.5 Control variables

5.5.1 Size

Alexandridis et al. (2013) find deal size to have a significant negative relationship with offer premia, which is in line with the lower overpayment potential in larger deals. They, however, also find deal size to negatively impact acquirer announcement returns, even when controlling for offer premia. Deal size therefore seems to also proxy deal complexity, which outweighs the positive effect of a potentially lower premium.

Deal size is included as variables c_SIZE and c_ABSSIZE in the further analysis, and we expect it to be negatively related to acquirer and target CAR as well as deal premia. Following on this logic, we also predict deal size to have a negative relationship with CWG, and, given the complexity aspect, also with deal completion. On the other hand, we expect a positive relation with ASOCWG due to the lower overpaying potential.

5.5.2 Relative Size

Gorton et al. (2009) find that for mid sized acquirers announcement returns announcement returns are negatively related to the size of the target relative to the acquirer. They argue their findings with relatively larger acquisitions being more difficult to finance for the acquirer. Other possible argumentations are that relatively larger targets might be more difficult to integrate or possibly have higher bargaining power in negotiations than relatively smaller targets. Fuller et al. (2002) also find a negative relationship between relative target size and acquirer announcement returns, albeit only for deals involving public targets. For deals involving private and subsidiary targets they find this relationship to be positive, which they reason with a larger share of merger gains accruing to the acquirer in private acquisitions, which seems to be magnified by increasing relative size. Golubov et al. (2012) find similar results and also find a negative relation between relative size and deal competition. This relation is only significant in the full sample and the public subsample, not so in the private subsample though.

Relative size is included as variable c_RELSIZE in the further analysis. We expect c_RELSIZE to be negatively related to acquirer CAR and deal competition. Based on this, we also predict c_RELSIZE to have a negative relation with ASOCWG due to the better negotiating position of the target. Effect on CWG is hard to estimate, due to the opposing effect of increased complexity and larger synergy potentials, thus we impose no prediction for the effect of c_RELSIZE and CWG.

5.5.3 Toehold

Toehold describes the acquirer already owning a sizable stake (usually 5% or more) in the target company prior to the acquisition. Ismail (2010) finds a significant negative relation between the toehold dummy and target wealth gain, and a positive but insignificant relation with acquirer wealth gain. He argues this with the toehold giving the acquirer a stronger negotiating position as well as possibly lower information asymmetry concerning the target's value. In line with other studies on the topic, Song et al. (2013) also finds toehold to have a significant negative impact on premium.

Toehold is included as variable c_TOEHOLD in the further analysis. We expect c_TOEHOLD to be negatively related to target CAR and premium and positively related to acquirer CAR. Assuming a stronger negotiating position, we also expect c_TOEHOLD to positively affect ASOCWG, and based on the lower information asymmetry assumption we predict a positive relation with deal completion. The relation with CWG is hard to predict, since while information asymmetry might have a positive impact, existing ownership might also imply that part of the potential synergies have already been realized, having a negative effect.

5.5.4 Public

Public targets usually have a wider ownership base than private one's, which could complicate negotiations. Furthermore public takeovers are likely to be subject to be more regulatory and public scrutiny, all of which makes it reasonable to expect the public / private status of a target to impact merger results. Indeed, Ertugrul & Krishnan (2011) report a significant negative impact of a target being public on acquirer CAR and the probability of completing a deal. These findings are in line with previous research such as Fuller et al. (2002), Moeller et al. (2004) or Ismail (2010). Golubov et al. (2012) argues that the impact of acquiring a public or private target should be dependent on the type of payment, as acquiring a closely held private target with shares would give the acquirer a large block-shareholder who possibly wants to interfere with management. This wouldn't be an issue with acquiring a private company with cash, nor with acquiring a widely held public company with stock.

Public is included as dummy variable c_PUBLIC in the further analysis, indicating deals where both acquirer and target are listed companies at deal announcement. We expect c_PUBLIC to be negatively related to acquirer CAR and the likelihood of completion. As some of the issues arising from dealing with public vs. with private targets can be expected to depend on payment type, the variable is interacted with c_SHARES in the acquirer sample. We also examine differences between public and private deals through subsampling (see Section 5.6).

5.5.5 Payment method

The type of payment method, cash, shares or a mixture of both, is frequently cited to impact merger outcomes. Amihud et al. (1990) present contrasting hypotheses for why target shareholders could have a preference for one or the other. Share payments usually are associated with tax advantages, whereas they also raise the issue of information asymmetry and signaling effects about the current valuation of the acquirer. Empirical results reflect the ambiguity of these hypotheses as some studies find positive, others negative impacts of share payments on merger outcomes. Ismail (2010) finds a significant negative (positive) relation between share (cash) bids and acquirer wealth gains, while Forte et al. (2010) find no significant relation and Ertugrul & Krishnan (2011) find a significant negative between all cash deals and acquirer CAR. Martynova & Renneboog (2009) study a European sample and find stock payment to be negatively related to acquirer return. Furthermore, stock payments could also add to deal complexity.

Payment method is included as variable c_SHARES in the further analysis, reflecting deals that include share in their payment. In the acquirer sample the impact of payment method is expected to depend on the public / private status of the target. c_SHARES is therefore interacted with c_PUBLIC. In the target sample the variables are included separately.

5.5.6 Run-up return

Based on the assumption, that investors' expectations and opinions are shaped by a companies' run-up returns, the stock return experienced by the target / acquirer during a certain time period prior to the announcement date, is found by multiple studies to impact merger returns. Rosen (2006) finds a significant negative relation between bidder's buy-and-hold abnormal return in the year prior to merger announcement and bidder CAR, in the later years (1990 - 2001) of his US sample, which is in line with the findings of Golubov et al. (2012). Rosen explains this pattern by stock price run-up resulting in overconfidence of management, potentially leading to hubris. In such cases, management will be more likely to offer a higher price for the target and pursue acquisitions that are value destroying.

Run-up abnormal buy-and hold return is included as variable c_RUNUP in the further analysis. We expect the run-up of the acquirer to be negatively related to acquirer CAR and ASOCWG, and to be positively related to premium. Following on the hubris argument, we further expect target run-up to be positively related to target CAR, as these companies are more likely to require a higher offer premium.

5.5.7 Cross industry

Acquirer and target operating in the same or different industry can impact negotiation dynamics and information asymmetry, thus it could impact merger outcomes. Kale et al. (2003) argue that acquirers have a bargaining advantage when acquiring business in related industries, compared to other deals. In their US sample (1981-1994), they find related business transactions to be positively related to acquirer and combined wealth gain and unrelated to target wealth gain, however, their results are insignificant at conventional levels. The relation between related business transactions and bidder's share of total wealth gain however, shows a significant positive relationship. Ismail (2010) and Song et al. (2013) have similar findings.

Industry effects are included as variable c_SIC for cross-industry transactions in the further analysis. We expect c_SIC to be negatively related to acquirer CAR, CWG and ASOCWG, and, based on the higher bargaining power assumption, we predict a positive relation of c_SIC with deal premium and target CAR. As cross industry deals tend to be more complicated, we predict a negative relation between c_SIC and deal completion.

5.5.8 Cross border

The impact of a deal being domestic or cross border is controversial in current research. Moeller & Schlingemann (2005) find that US acquirers experience lower announcement returns for deals involving foreign targets compared to domestic ones and Conn et al. (2005) have similar findings for UK acquirers. In a study on UK targets, Danbolt (2004) finds no statistically significant difference in announcement returns, and ascribes differences to other bid characteristics differing between domestic and cross border deals. On the other hand, in a Europe wide study, Goergen & Renneboog (2004) find significant positive effect of cross border deals on target announcement returns and no significant impact of cross border deals on acquirer announcement returns.

Cross border is included as dummy variable c_CROSSB in the further analysis, which we expect to be negatively related to acquirer CAR and positively to target CAR. We further predict c_CROSSB to have a negative impact on ASOCWG, and given the increased complexity, also on deal completion.

5.5.9 Number of advisers

The number of advisers working on either side of a deal could potentially impact deal dynamics, but can also be a proxy for deal complexity. Hunter & Jagtiani (2003) investigate US mergers between 1995 and 2000 and find the number of target and acquirers advisers has a significant positive impact on the probability of closing a deal and on time to completion (i.e. longer deal duration). They also find a significant positive impact of the number of acquirer advisers on acquirers' acquisition gains.

Number of advisers is included as variables c_ADV_NR_a and c_ADV_NR_t in the further analysis. We expect the number of acquirer (target) advisers to be positively related to acquirer (target) CAR and negatively to target (acquirer) CAR. Furthermore we expect a positive impact on time to completion and the likelihood of deal completion.

5.5.10 Deal nature and deal type

The most commonly applied control for deal nature is the hostile dummy. Hostile deals are likely to be more complex and have different dynamics than friendly deals. Schwert (2000) argues that there are different degrees of hostility, rather than it being clear cut to define a deal as hostile. Furthermore he finds that many deals described as hostile by the press are economically no different from supposedly friendly deals, except for them including publicity in the bargaining process. Nonetheless prior studies have found significant impact of a deal being hostile on different measures of deal outcome. Ismail

(2010) find that a deal being hostile has a significant positive impact on deal premia and Ertugrul & Krishnan (2011) find friendly deals (the counterpoint to hostile deals) to have a significant positive impact on acquirer CAR.

Hostile deals are included as variable c_HOSTILE in the further analysis. We expect c_HOSTILE to be negatively related to acquirer CAR and positively related to target CAR and premium. Based on this, we further expect hostile deals to have a negative impact on ASOCWG and deal completion. On the same ground we also include controls for unsolicited bids (c_UNSOLICITED) and contested bids (c_CONTESTED), and expect the same relations as for c_HOSTILE. In addition, to increase the explanatory power of the regressions, we also include controls for deal type, such as private equity exits and leveraged buyouts. The detailed list and description of these deal type variables are presented in Table 6.

5.5.11 Merger momentum

Based on the neoclassical theory of mergers, which assumes merger waves to be caused by economic shocks that create new synergy opportunities, and the managerial theory which assumes that merger waves are more driven by empire building, Rosen (2006) investigates the impact of merger waves on merger outcomes. Depending on which theory holds true the impact of merger waves can be expected to be positive (neoclassical) or negative (managerial theory) for acquiring firms. Rosen (2006) finds differing results for different measures of merger momentum. While trailing 12-month average CAR has a significant positive impact, trailing 12-month number of mergers has a significant negative impact on acquirer CAR in his US sample covering the period between 1990 and 2001. Year fixed effects used by many other studies proxy similar effects, however in less specificity.

Merger waves are included as variables c_T6M_NR (trailing 6-month number of deals), c_T6M_CAR (trailing 6-month average acquirer / target CAR) and c_T6M_PREMIUM (trailing 6-month average premium), as well as through year fixed effects in the further analysis. Given the relative short time period of our study we consider a trailing 6-month horizon more appropriate than Rosen's 12-month horizon. We expect c_T6M_NR to be negatively related to acquirer CAR and the c_T6M_CAR and c_T6M_PREMIUM to be positively related to acquirer and target CAR and premium.

5.5.12 Variable definition

Table 6 provides an overview of the definition of all control variables included in the analysis.

Table 6: Control variables

This table presents the definition and derivation of each of the control variables used in our analysis. The pre-term 'c_' signals the control variable nature of the below measures, and is omitted in the text when discussing results but presented in the regression tables. c_RELSIZE is only included in the acquirer sample regressions, given that acquirer market cap is needed to calculate this ratio. c_ABSSIZE is included only in the CWG regressions, as a substitute for c_SIZE. c_YEAR and T6M variables are never included in a regression simultaneously, and are considered to proxy for similar market movements.

Control variable	Variable definition
c_SIZE	c_SIZE is defined as the natural logarithm of deal value in EUR thousand.
c_ABSSIZE	c_ABSSIZE is defined as the deal value denominated in EUR million. The variable is created to replace c_SIZE in the ASOCWG regression as it measures absolute value rather than a standardized value.
c_RELSIZE	c_RELSIZE is defined as the fraction of deal value (denominated in EUR thousand as downloaded from Zephyr) and the market value of the acquirer 20 trading days (approximately 1 month) before the announcement date, converted to EUR using the exchange rate of the respective date as provided by Datastream.
c_TOEHOLD	c_TOEHOLD is a dummy variable equal to 1 if the initial stake in the target being held by the acquirer before the acquisition being larger than 5% according to the Zephyr database and 0 otherwise. If the initial stake is indicated as *Unknown minority* the dummy variable is set equal to 0.
c_PUBLIC	c_PUBLIC is a dummy variable equal to 1 if both target and acquirer are listed, and 0 otherwise. For transaction with multiple targets / acquirers the dummy is equal to 1 if at least on party on each side of the transaction is listed.
c_SHARES	c_SHARES is a dummy equal to 1 if the type of payment in the Zephyr data base includes *Shares* and 0 otherwise.
c_RUNUP	c_RUNUP is defined as the buy and hold abnormal return (BHAR) across the estimation window, calculated based on the market model estimated in the event study.
c_SIC	c_SIC is a dummy variable equal to 1 if target and acquirer have the same primary 4-digit SIC code as stated in the Zephyr database, and 0 otherwise. For transactions with multiple targets / acquirers with the dummy is 0 if one of the parties has a SIC code different from the other parties involved in the transaction.
c_CROSSB	c_CROSSB is a dummy variable equal to 1 if target and acquirer are located in different countries and 0 if they are located in the same. For transactions with multiple targets / acquirers the dummy is equal to 1 if one of the involved parties is located in a country different from the others.
c_ADV_NR_a	c_ADV_NR_a is defined as the number of financial advisers hired by the acquirer in a given deal as included in the Zephyr database.

c_ADV_NR_t	c_ADV_NR_t is defined as the number of financial advisers hired by the target in a given deal as included in the Zephyr database.
c_HOSTILE c_CONTESTED c_UNSOLICITED	c_HOSTILE, c_CONTESTED and c_UNSOLICITED are dummy variables equal to 1 if the deal subtype in the Zephyr database is *Hostile bid*, *Contested bid* or *Unsolicited bid*, respectively, and 0 otherwise.
c_SOA c_EXIT c_LBO c_ASSET c_REORG	c_SOA, c_EXIT, c_LBO, c_ASSET and c_REORG are deal type dummy variables equal to 1 if the deal subtype in the Zephyr database is *Scheme of arrangement*, *Exit / Exit - Partial*, *Leveraged buy out*, *Asset sale* or *Restructuring*, respectively. For all other transactions the dummy equals 0.
c_YEAR	c_YEAR is a fixed effect variable based on the announcement date of the transaction.
c_T6M_NR	c_T6M_NR is defined as the number of deals that have been announced within 6 month prior to the announcement date of the deal, divided by 1,000.
c_T6M_CAR	c_T6M_CAR is defined as the average CAR across all deals in the respective sample that were announced within 6 month prior to the announcement date of the deal.
c_T6M_PREMIUM	c_T6M_PREMIUM is defined as the average PREMIUM across all deals in the respective sample that were announced within 6 month prior to the announcement date of the deal.
c_COUNTRY	c_COUNTRY is a fixed effect variable based on the country of the acquirer in the acquirer sample and based on the country of the target in the target sample.

5.6 Subsamples

Besides running our analysis on the full merger sample described earlier, we subset the full sample into different subsets to be able to examine relation between advisers and M&A outcomes in different settings. The full sample includes announced deals of all completion statuses. Prior studies vary between investigating announced or completed deals. The main measure of value creation analyzed in this paper is announcement return, and on announcement date deals that eventually are being closed are not distinguishable from deals which eventually fail. Therefore including all completion statuses should give a better understanding of adviser impact on announcement return rather than just including completed deals. For certain dependent variables, which are contingent upon deal completion (Premium and Deal completion probability) a completed sample is the logical choice. Zephyr does not fully update the current status of all deals, as such, only deals marked *Completed* or *Completed Assumed* are included in the completed subsample. All other deals are lumped into the *Non-completed* subsample as included in Tables 7 and 8. As this combination of still pending, withdrawn and deals with unknown outcome is not meaningful, this sample is not analyzed further.

Whether a private or public target is acquired in an acquisition is found to have a significant impact on merger results by multiple studies, thus we include it as control in our full sample regression. However, there are reasons to expect that the effect of this is different depending on whether shares are used as method of payment or whether the transaction is fully settled in cash. Chang (1998) presents three hypotheses to that effect, suggesting differing impact of taking over a private target depending on the method of payment used. E.g. paying for a private company with shares usually makes the target owners a sizeable blockholder in the acquirer, while with a public company with dispersed company most likely would just be multiple small new shareholders in the acquirer, likely triggering different merger announcement reactions. On the other hand under cash payment this would not be an issue. Several US studies on the impact of adviser reputation on M&A performance have therefore chosen to run their analysis also on public / private subsamples and Golubov et al. (2012) find adviser reputation to impact acquirer CAR only in public deals, but not in private ones.
We are not aware of any studies investigating private and public acquirer subsamples. Most studies investigate listed acquirers only and moreover the impact of public vs. private acquirer being dependent on the payment method seems unlikely to hold in a similar way as it does for the acquirer sample. Nonetheless we believe that it could be worthwhile to analyze these subsamples, as the perception of a private vs. a public acquirer might differ for other characteristics, beyond payment type.

Table 7 and 8 provide an overview of the values of the different control variables across the subsamples in the acquirer and target sample respectively.

Table 7: Variables across sub-samples - Acquirer sample

This table provides an overview of the values of the different variables across the subsamples in the acquirer sample. For non-dummy varibles mean and median are provided, while for dummy variables mean and sum are provided. The column "Sum" presents the number of deals in the sample, for which the dummy variable takes a value of one. In addition p-values for differences in mean between the subsamples are presented. The number of deals in each sample is provided as reference point.

	Full sample		Completed		Non-completed		Public		Private			
Sample size	1,037		931		106		312		725			
											Mean difference p-value	
Non-dummy Variable	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Completed vs. Non-completed	Public vs. Private
CAR	0.021	0.015	0.024	0.019	−0.010	−0.014	−0.007	−0.004	0.033	0.025	0.000	0.000
c_SIZE	11.976	11.870	11.804	11.744	13.482	13.584	13.406	13.469	11.361	11.303	0.000	0.000
c_RELSIZE	0.571	0.282	0.527	0.263	0.952	0.696	0.711	0.497	0.510	0.232	0.000	0.000
c_RUNUP	1.872	1.264	1.772	1.270	2.742	1.212	1.032	1.217	2.233	1.287	0.604	0.211
c_ADV_NR_a	0.991	1.000	0.932	1.000	1.509	1.000	1.587	1.000	0.735	1.000	0.000	0.000
c_ADV_NR_t	0.567	0.000	0.463	0.000	1.481	1.000	1.391	1.000	0.212	0.000	0.000	0.000
c_T6M_NR	0.779	0.742	0.777	0.740	0.796	0.746	0.796	0.752	0.772	0.737	0.506	0.198
c_T6M_CAR	0.010	0.012	0.010	0.012	0.010	0.013	0.011	0.013	0.010	0.012	0.992	0.312
											Mean difference p-value	
Dummy Variable	Mean	Sum	Mean	Sum	Mean	Sum	Mean	Sum	Mean	Sum	Completed vs. Non-completed	Public vs. Private
TIER1_a	0.313	325	0.294	274	0.481	51	0.513	160	0.228	165	0.000	0.000
TIER1_t	0.195	202	0.157	146	0.528	56	0.506	158	0.061	44	0.000	0.000
c_PUBLIC	0.301	312	0.246	229	0.783	83	1.000	312	0.000	0	0.000	n.a.
c_SHARES	0.528	548	0.513	478	0.660	70	0.660	206	0.472	342	0.003	0.000
c_TOEHOLD	0.088	91	0.086	80	0.104	11	0.151	47	0.061	44	0.568	0.000
c_SIC	0.641	665	0.650	605	0.566	60	0.567	177	0.673	488	0.102	0.001
c_CROSSB	0.400	415	0.398	371	0.415	44	0.381	119	0.408	296	0.744	0.417
c_HOSTILE	0.026	27	0.003	3	0.226	24	0.087	27	0.000	0	0.000	0.000
c_CONTESTED	0.049	51	0.016	15	0.340	36	0.154	48	0.004	3	0.000	0.000
c_UNSOLICITED	0.014	14	0.004	4	0.094	10	0.038	12	0.003	2	0.002	0.001
c_SOA	0.074	77	0.067	62	0.142	15	0.237	74	0.004	3	0.034	0.000
c_EXIT	0.119	123	0.128	119	0.038	4	0.074	23	0.138	100	0.000	0.001
c_LBO	0.019	20	0.018	17	0.028	3	0.022	7	0.018	13	0.550	0.644
c_ASSET	0.011	11	0.011	10	0.009	1	0.003	1	0.014	10	0.896	0.050
c_REORG	0.004	4	0.004	4	0.000	0	0.006	2	0.003	2	0.045	0.459

Table 8: Variables across sub-samples - Target sample

This table provides an overview of the values of the different variables across the subsamples in the target sample. For non-dummy varibles mean and median are provided, while for dummy variables mean and sum are provided. The column "Sum" presents the number of deals in the sample, for which the dummy variable takes a value of one. In addition p-values for differences in mean between the subsamples are presented. The number of deals in each sample is provided as reference point.

	Full sample		Completed		Withdrawn		Public		Private			
Sample size	407		263		144		201		206			
											Mean difference p-value	
											Completed vs.	Public vs.
Non-dummy Variable	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Non-completed	Private
CAR	0.109	0.075	0.105	0.062	0.115	0.093	0.099	0.075	0.118	0.075	0.516	0.164
c_SIZE	13.520	13.379	13.276	13.261	13.967	13.617	13.675	13.476	13.369	13.345	0.001	0.110
c_RUNUP	−0.164	1.222	1.007	1.157	−2.303	1.598	0.911	1.260	−1.213	1.205	0.364	0.414
c_ADV_NR_a	1.541	1.000	1.540	1.000	1.542	1.000	1.721	1.000	1.364	1.000	0.989	0.003
c_ADV_NR_t	1.641	1.000	1.525	1.000	1.854	1.000	1.622	1.000	1.660	1.000	0.043	0.794
c_T6M_NR	0.788	0.734	0.787	0.726	0.789	0.746	0.822	0.776	0.755	0.590	0.928	0.013
c_T6M_CAR	0.100	0.104	0.098	0.101	0.105	0.111	0.093	0.094	0.108	0.114	0.164	0.003
											Mean difference p-value	
											Completed vs.	Public vs.
Dummy Variable	Mean	Sum	Mean	Sum	Mean	Sum	Mean	Sum	Mean	Sum	Non-completed	Private
TIER1_a	0.558	227	0.574	151	0.528	76	0.587	118	0.529	109	0.371	0.240
TIER1_t	0.570	232	0.525	138	0.653	94	0.607	122	0.534	110	0.011	0.138
c_PUBLIC	0.494	201	0.532	140	0.424	61	1.000	201	0.000	0	0.036	n.a.
c_SHARES	0.344	140	0.380	100	0.278	40	0.627	126	0.068	14	0.034	0.000
c_TOEHOLD	0.226	92	0.236	62	0.208	30	0.209	42	0.243	50	0.523	0.416
c_SIC	0.592	241	0.612	161	0.556	80	0.557	112	0.626	129	0.271	0.158
c_CROSSB	0.275	112	0.247	65	0.326	47	0.333	67	0.218	45	0.096	0.010
c_HOSTILE	0.120	49	0.030	8	0.285	41	0.124	25	0.117	24	0.000	0.808
c_CONTESTED	0.165	67	0.076	20	0.326	47	0.149	30	0.180	37	0.000	0.410
c_UNSOLICITED	0.081	33	0.030	8	0.174	25	0.090	18	0.073	15	0.000	0.538
c_SOA	0.263	107	0.278	73	0.236	34	0.244	49	0.282	58	0.358	0.388
c_EXIT	0.032	13	0.042	11	0.014	2	0.025	5	0.039	8	0.077	0.423
c_LBO	0.034	14	0.015	4	0.069	10	0.020	4	0.049	10	0.017	0.112

6 Results

6.1 CAR

Tables 9 and 10 present our results on examining the relationship between adviser reputation and announcement returns. Both tables include five regressions. Regression (1) is the simplest version of the five, including only the Tier 1 dummies as explanatory variables. We present this setup for the sake of comparability with some of the earliest studies that did not include control variables for deal, market or acquirer characteristics. Regression (2) includes the general control variables and (3) adds the deal nature and deal type controls. (4) and (5) each include the country fixed effects as a further control, with (4) also introducing year fixed effects. In (5) we swap the year fixed effects to T6M_NR and T6M_CAR (the number and average CAR of deals announced in the last six months) to test the merger momentum effects documented by Rosen (2006). The different regression setups also allow us to examine the persistence of our results.

As a first step, we focus on dummies TIER1_a (in the acquirer sample) and TIER1_t (in the target sample) and test Hypothesis 1a: *Acquirers (targets) hiring at least one Tier 1 adviser realize higher announcement abnormal returns than acquirers (targets) who do not hire Tier 1 advisers.* In the acquirer sample, in contrast to our expectation, TIER1_a shows a negative relationship with acquirer announcement CARs, with the coefficients being significant in regression (1) through (3). However, the significance level decreases as we introduce more controls, and eventually disappears in regressions (4) and (5), after we include fixed effects and merger wave proxies. Our results suggest that the acquirer hiring a Tier 1 adviser decreases acquirer CAR by c. 1.3pp, on average, an economically relevant impact when compared to the mean (median) acquirer CAR of 2.1% (1.5%). One possible interpretation of our observations is that acquirer advisers, in line with the deal completion hypothesis, focus on closing, thus client wealth gains become secondary objectives. The negative impact on CAR can result from offering a larger share of synergies to the target, or from executing deals that generate lower total synergies. We will revisit these questions in the analysis of CWG, ASOCWG and deal premia in the following subsections. Note, however, that the negative coefficient does not necessarily imply a negative acquirer CAR (i.e. does not mean value destroying deals for acquirer shareholders), and that, offering a higher premium can also be a result of a higher quality or strategically important target.

Table 9: Adviser reputation and acquirer CAR

This table presents our OLS regression results on the relationship between adviser reputation and acquirer announcement abnormal returns. The sample includes both public and private targets, for the separate regressions on the public and private subsamples please refer to Appendix A.3. In order to decrease the impact of noise and make CAR measurement more reliable, we excluded transactions with a deal value representing less than 10% of the acquirer's market capitalization. Both completed and non-completed deals are included in the analysis. Mean (median) acquirer CAR in the sample is 2.1% (1.5%). The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	Dependent variable:				
	CAR				
	(1)	(2)	(3)	(4)	(5)
Constant	0.0297***	0.0223	0.0180	−0.0009	0.0333
	(0.0031)	(0.0176)	(0.0176)	(0.0276)	(0.0250)
m_TIER1_a	−0.0146**	−0.0129*	−0.0135*	−0.0085	−0.0109
	(0.0063)	(0.0073)	(0.0073)	(0.0072)	(0.0073)
m_TIER1_t	−0.0308***	−0.0035	−0.0018	0.0088	0.0068
	(0.0095)	(0.0109)	(0.0110)	(0.0114)	(0.0112)
m_TIER1_a:m_TIER1_t	0.0119	0.0082	0.0069	−0.0003	0.0017
	(0.0120)	(0.0124)	(0.0125)	(0.0129)	(0.0126)
c_SIZE		0.0003	0.0006	0.0002	−0.0002
		(0.0016)	(0.0016)	(0.0016)	(0.0016)
c_RELSIZE		0.0092***	0.0095***	0.0093***	0.0096***
		(0.0031)	(0.0032)	(0.0031)	(0.0031)
c_TOEHOLD		−0.0125	−0.0114	−0.0147*	−0.0111
		(0.0083)	(0.0084)	(0.0084)	(0.0088)
c_PUBLIC		−0.0135*	−0.0102	−0.0113	−0.0121*
		(0.0069)	(0.0070)	(0.0075)	(0.0073)
c_SHARES		0.0031	0.0037	0.0046	0.0041
		(0.0059)	(0.0059)	(0.0060)	(0.0059)
c_PUBLICTRUE:c_SHARES		−0.0324***	−0.0333***	−0.0353***	−0.0358***
		(0.0094)	(0.0094)	(0.0097)	(0.0095)
c_RUNUP		0.0001	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0002)	(0.0002)
c_SIC		0.0057	0.0055	0.0072	0.0078
		(0.0047)	(0.0047)	(0.0048)	(0.0048)
c_CROSSB		−0.0017	−0.0019	−0.0062	−0.0060
		(0.0048)	(0.0049)	(0.0051)	(0.0051)
c_ADV_NR_a		0.0030	0.0023	0.0018	0.0027
		(0.0026)	(0.0027)	(0.0028)	(0.0028)
c_ADV_NR_t		−0.0046*	−0.0043	−0.0038	−0.0039
		(0.0027)	(0.0029)	(0.0029)	(0.0029)
c_HOSTILE			−0.0237**	−0.0185	−0.0224*
			(0.0120)	(0.0118)	(0.0122)
c_CONTESTED			−0.0112	−0.0135	−0.0112
			(0.0098)	(0.0105)	(0.0102)
c_UNSOLICITED			−0.0136	−0.0126	−0.0063
			(0.0139)	(0.0141)	(0.0134)
c_SOA			0.0052	0.0044	0.0086
			(0.0089)	(0.0095)	(0.0093)
c_EXIT			0.0014	0.0023	0.0026
			(0.0067)	(0.0066)	(0.0067)
c_LBO			0.0069	0.0006	0.0001
			(0.0172)	(0.0180)	(0.0161)
c_ASSET			0.0374**	0.0387**	0.0389*
			(0.0190)	(0.0196)	(0.0199)
c_REORG			−0.0540*	−0.0481	−0.0468
			(0.0294)	(0.0336)	(0.0321)
c_T6M_NR					−0.0064
					(0.0089)
c_T6M_CAR					0.8656***
					(0.2718)
Fixed effects	No	No	No	Year, Country	Country
F Statistic	13.6359***	7.6298***	5.8953***	3.6702***	4.0900***
Observations	1,037	1,037	1,037	1,037	1,037
R^2	0.0290	0.0879	0.0975	0.1479	0.1287
Adjusted R^2	0.0262	0.0754	0.0780	0.1038	0.0955
Residual Std. Error	0.0747	0.0728	0.0727	0.0716	0.0720

*p<0.1; **p<0.05; ***p<0.01

Table 10: Adviser reputation and target CAR

This table presents our OLS regression results on the relationship between adviser reputation and target announcement abnormal returns. The sample includes both public and private acquirers, for the separate regressions on the public and private subsamples please refer to Appendix A.3. Both completed and non-completed deals are included in the analysis. Mean (median) target CAR in the sample is 10.9% (7.5%). The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	Dependent variable:				
	CAR				
	(1)	(2)	(3)	(4)	(5)
Constant	0.1024***	0.3011***	0.3159***	0.2421**	0.2357**
	(0.0117)	(0.0623)	(0.0605)	(0.1179)	(0.1013)
m_TIER1_a	0.0302	0.0466**	0.0504**	0.0584**	0.0514**
	(0.0204)	(0.0221)	(0.0229)	(0.0246)	(0.0233)
m_TIER1_t	0.0409*	0.0774***	0.0748***	0.0828***	0.0754***
	(0.0235)	(0.0278)	(0.0268)	(0.0306)	(0.0281)
m_TIER1_a:m_TIER1_t	−0.0833***	−0.0732**	−0.0675**	−0.0723**	−0.0643**
	(0.0308)	(0.0334)	(0.0318)	(0.0346)	(0.0323)
c_SIZE		−0.0147***	−0.0178***	−0.0177***	−0.0160***
		(0.0052)	(0.0052)	(0.0061)	(0.0058)
c_TOEHOLD		−0.0523***	−0.0458***	−0.0377**	−0.0389**
		(0.0152)	(0.0151)	(0.0157)	(0.0156)
c_PUBLIC		0.0089	0.0160	0.0177	0.0178
		(0.0169)	(0.0165)	(0.0181)	(0.0176)
c_SHARES		−0.0459***	−0.0492***	−0.0488***	−0.0540***
		(0.0172)	(0.0170)	(0.0187)	(0.0181)
c_RUNUP		0.0004**	0.0006***	0.0006***	0.0005***
		(0.0001)	(0.0001)	(0.0002)	(0.0002)
c_SIC		0.0143	0.0176	0.0262*	0.0225
		(0.0141)	(0.0143)	(0.0145)	(0.0144)
c_CROSSB		0.0111	0.0093	0.0073	0.0071
		(0.0157)	(0.0151)	(0.0157)	(0.0154)
c_ADV_NR_a		−0.0110	−0.0096	−0.0142**	−0.0115*
		(0.0068)	(0.0067)	(0.0071)	(0.0069)
c_ADV_NR_t		−0.0033	−0.0021	0.0012	−0.0001
		(0.0045)	(0.0045)	(0.0047)	(0.0045)
c_HOSTILE			0.0053	−0.0119	−0.0158
			(0.0191)	(0.0209)	(0.0211)
c_CONTESTED			0.0168	0.0202	0.0143
			(0.0186)	(0.0208)	(0.0205)
c_UNSOLICITED			0.0282	0.0282	0.0318
			(0.0264)	(0.0296)	(0.0283)
c_SOA			0.0148	−0.0094	−0.0124
			(0.0165)	(0.0269)	(0.0246)
c_EXIT			0.0019	−0.0049	0.0054
			(0.0406)	(0.0403)	(0.0387)
c_LBO			0.1570***	0.1663***	0.1474***
			(0.0435)	(0.0517)	(0.0455)
c_T6M_NR					−0.0210
					(0.0252)
c_T6M_CAR					−0.0108
					(0.1360)
Fixed effects	No	No	No	Year, Country	Country
F Statistic	2.6997**	5.2692***	4.6378***	2.7055***	3.3694***
Observations	407	407	407	407	407
R^2	0.0223	0.1174	0.1635	0.2307	0.2076
Adjusted R^2	0.0150	0.0905	0.1247	0.1300	0.1352
Residual Std. Error	0.1386	0.1332	0.1307	0.1303	0.1299

*p<0.1; **p<0.05; ***p<0.01

To examine the patterns discussed by Golubov et al. (2012), that is adviser reputation matters more in public deals, we also run the regressions for the public and private subsamples separately. We find that while the coefficient of TIER1_a remains negative in both subsets, it only gains significance in the private subsample, in contrast to Golubov et al.'s findings. (Subsample regressions are presented in Table A.3 within Appendix A.3).

Looking at the target sample we observe very different results. TIER1_t shows a positive sign already in regression (1), significant at the 10% level, and both coefficient and significance increase after controlling for deal characteristics, deal types and merger momentum. Hiring a Tier 1 adviser on the target side is associated with a 7.5pp - 8.3pp increase in CAR for target companies, and these findings are significant at the 1% level. The results are also economically relevant when comparing them to the mean (median) target CAR of 10.9% (7.5%) observed in our sample. This empirical evidence provides support for Hypothesis 1a in the target sample.

The lower significance level observed in the acquirer sample can result from multiple factors. On one hand, the mean (median) announcement CAR in the sample is relatively low, 2.1% (1.5%) compared to 10.9% (7.5%) in the target sample, making it more difficult to measure acquirer CAR reliably due to 'noise'. Listed companies' stock price can be affected by various events and market movements, which are hard to control for. Furthermore, the timing of corporate announcements can also be an issue. In section 7 Robustness tests, we run sensitivity tests in an attempt to explore potential ways of improvement for our CAR estimation and acquirer CAR regressions. We find that increasing the relative deal size condition from 10% to 20% of the acquirer's market cap results in a significant negative coefficient of TIER1_a across all regressions in the acquirer sample, while decreasing it to 5% erases the significance. We attribute these results to higher relative size increasing the importance of the transaction for the acquirer, thus easing CAR measurement around announcement.

Moving on to the analysis of cross-side effects of adviser reputation, we examine TIER1_t (in the acquirer sample) and TIER1_a (in the target sample) to test Hypothesis 1b: *Acquirers (targets) realize lower announcement abnormal returns if the target (acquirer) hires at least one Tier 1 adviser.* In the acquirer sample, we can not find empirical support for Hypothesis 1b. While the coefficient of TIER1_t is negative and significant in regression (1), the significance disappears already after introducing our first set of controls, and adding fixed effects and merger momentum variables turns the coefficient into positive but insignificant.

The target sample shows more promising, however, surprising results. In contrast to our expectations under Hypothesis 1b, TIER1_a has a positive coefficient in regressions (2) through (5), significant at the 5% level. This suggests that the acquirer hiring a Tier 1 adviser increases target CAR by 4.6pp - 5.8pp, on average, and the effect is also economically relevant compared to the mean (median) target announcement CAR of 10.9% (7.5%). This contradicts our prediction that the acquirer hiring a Tier 1 adviser effects target returns negatively. One potential interpretation of the results is that acquirer advisers, in line with the deal completion hypothesis, focus on deal completion rather than acquirer wealth gain, and offer a higher price for the target, in order to secure deal completion. This interpretation is in line with our findings in the acquirer sample, and we will further examine deal completion implications directly in Section 6.4.

Apart from the pure effect of either party hiring a Tier 1 adviser, we also examine the interaction effect between Tier 1 advisers. The interaction term (TIER1_a:TIER1_t) represents the incremental effect of both sides hiring Tier 1 advisers. In the acquirer sample, we observe no significant relation between TIER1_a:TIER1_t and acquirer CAR, a not so surprising result, given the generally weaker significance present in the acquirer regression. The target sample, however, shows a significant negative interaction term. Both sides hiring Tier 1 advisers decreases target CAR by 6.4pp - 7.3pp, on average, compared to the situation where only one party hires a Tier 1 adviser. Our results are significant at the 5% level and are also economically relevant when compared to the mean and median target return (10.9% and 7.5%), as well as compared to the individual adviser effects (4.7% - 8.3%). We interpret this pattern as Tier 1 advisers adding complexity to deal processes and negotiation, which effect is magnified when both acquirer and target retain Tier 1 advisers. Assuming that Tier 1 advisers have skill advantage over non-Tier 1 advisers, they can easily create value for both parties as they can easily take the leading role and facilitate the transaction efficiently. However, value creation and negotiation becomes harder when the other party engages an adviser with a similar skill level. As competences, in such situations, even out, it is harder for either adviser to seize the lead position, which can slow down or complicate processes.

In addition to analyzing adviser reputation, our regressions also provide an opportunity to examine how certain deal and firm characteristics effect acquirer and target announcement returns. Observing significant results in control variables, that are interpretable and similar to the findings of existing studies, supports the validity of our models.

SIZE has a negative coefficient in the target sample, through all regressions, significant at the 5% level. This is in line with the findings of Alexandridis et al. (2013), that larger deals have lower overpayment potential, thus deal size has a negative effect on premium, eventually also affecting target CAR negatively. Conversely, a positive impact is observed on acquirer CAR in regressions (2) to (4), however, these results are not significant. RELSIZE has significant and positive coefficient in the acquirer CAR regressions in the full sample, however, when looking at the private and public subsamples, we observe similar patterns as documented by Fuller et al. (2002). The significant positive relationship between acquirer returns and deal size persists only in the public subsample, while the coefficient of RELSIZE turns negative in the public subsample, although remains insignificant. As mentioned earlier, Fuller et al. (2002) explain this with the acquirer having better negotiation position in private deals and thus seizing larger proportion of total synergies, and this effect is magnified by size. In public setups, however, the complexity aspects become more pronounced, affecting CARs negatively.

Our results show a significant negative relationship between TOEHOLD and target returns, in line with the findings of Ismail (2010), explained by existing ownership giving a better negotiation position for the acquirer. It can also be interpreted as a result of lower information asymmetry, that promises a better, more thought-through merger.

The negative coefficient of the PUBLIC dummy in the acquirer sample supports the proposition that inherent complexity of public deals mitigate some of the synergistic gains, thus decreasing acquirer returns. It can also be interpreted as public targets requiring larger deal premium, supported by the positive (although insignificant) coefficients observed in the target sample. The interaction term between the PUBLIC and SHARE dummies shows a significant negative impact, suggesting that complexity is amplified for share payments in public settings. While SHARES has a positive but insignificant coefficient in the acquirer sample, it shows a significant negative coefficient in the target sample, suggesting target shareholder's preference for cash payments.

In line with expectations, hostile deals generate significantly lower acquirer returns, although opposite patterns are not observed in the target sample. RUNUP has a significant positive impact on target CARs, suggesting that companies performing well in the year before the acquisition are expected to realize an amplifying effect through the merger, or are able to negotiate a higher price given their recent track record. Following from the arguments of Rosen (2006), it can also be interpreted as the run-up of target stocks leading to overconfidence of management, who in turn will require higher premium, positively affecting CAR. Our variables proxying merger momentum show patterns similar to that observed by Rosen (2006): acquirer abnormal returns are positively related to last six months average acquirer CAR (significant at the 1% level) and negatively related to the number of transactions announced during this period.

6.2 Combined wealth gain and split of combined wealth gain

Table 11 presents our results on the relationship between adviser reputation and combined wealth gains as well as the split of combined wealth gains in M&A deals. Both dependent variables require for target and acquirer to be listed and sufficient data for the calculation of cumulative announcement returns to be available. This requirement decreases the sample size substantially, compared to the listed acquirer and the listed target samples. To avoid overspecification issues, we abstained from including year or country fixed effects in the regressions and instead only used the regression set ups applied in regressions (2) and (3) in Tables 9 and 10 on CAR. Given the potential structural differences between the countries and documented impact of merger waves on announcement CAR, we consider the addition of such controls an interesting extension, that our sample size, however, does not allow for.

Regression (1) and (2) in Table 11 test Hypothesis 2: *Deals, where at least one Tier 1 adviser is hired by either party, generate higher combined wealth gains than deals where no Tier 1 adviser is hired.*. To be able to examine Hypothesis 2, we combined the variables TIER1_a and TIER1_t into one, united variable, TIER1, which equals 1 for deals where either the acquirer, the target or both hire a Tier 1 adviser. TIER1 has a positive coefficient in both regressions, suggesting that Tier 1 advisers do generate higher combined gains in M&A deals, however, the results of the regression are not significant at conventional levels. After controlling for deal type, the coefficient of TIER 1 decreases in regression (2), possibly indicating that part of the wealth gain attributed to Tier 1 advisers in regression (1) actually stems from advising on specific deal types, rather than being a result of adviser value creation. However, given the small sample size, insignificant coefficients and the insignificance of the full model, we can neither support nor negate Hypothesis 2.

While none of the control variables show a significant relation to combined wealth gain in either of the two regressions, the sign of the coefficients are mostly in line with the findings of existing studies. Since combined wealth gain is calculated as an absolute measure, ABSSIZE (absolute deal size) is included instead of SIZE (logarithmic deal size) used in all other regressions. In line with expectations, deal size shows a positive coefficient, as larger deals, on average, have larger absolute value creation potential. RELSIZE is positively related to combined wealth creation, suggesting that completing a comparably larger deal increases synergy potential, outweighing the negative effects of increased complexity and potential integration difficulties. TOEHOLD, which was found to have a significant positive impact on combined wealth gain in Kale et al.'s (2003) US study, has an insignificant negative coefficient in our sample. SHARES has a negative coefficient, which is in line with the significant negative relation found by Ismail (2010). Diversifying deals have a positive relation with combined wealth gain, indicating a possibly higher synergy potential from complementary acquisitions as compared to same industry deals. HOSTILE dummy has a negative impact on CWG, which can be interpreted as increased complexity, acquirer effort or uncertainty.

Regression (3) and (4) in Table 11 examine the relation between adviser reputation and the acquirer's share of the combined wealth gains (ASOCWG). The regressions explore Hypotheses 3a: *Acquirers hiring at least one Tier 1 adviser receive a larger share from the combined wealth gain generated through the merger than acquirers that do not hire Tier 1 advisers.* and 3b: *Acquirers receive a smaller share from the combined wealth gain if the target hires at least one Tier 1 adviser.* Facing the same small sample issue as with regressions (1) and (2) when examining CWG, we find no significant relationship between the TIER1 dummies and ASOCWG, thus we can not confirm nor negate neither of the two hypotheses. Looking at the signs of the coefficients, they seem to contradict our earlier findings that both acquirer and target advisers have positive effect on target CAR, which we interpreted as offering a higher price in order to ensure completion, together leading to a lower ASOCWG. While a higher CWG could still explain the si-

Table 11: Adviser reputation and CWG / ASOCWG

This table presents our OLS regression results on the relationship between adviser reputation and combined wealth gains as well as the split of combined wealth gains in M&A deals. Both dependent variables, require for target and acquirer to be listed and sufficient data for the calculation of cumulative announcement returns to be available, which decreases the sample size substantially. To avoid overspecification issues we abstained from including year of country fixed effects in the regressions. For the analysis of CWG the variables TIER1_a and TIER1_t were combined to dummy TIER1, which is equal to one for all deals involving at least 1 Target adviser. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	Dependent variable:			
	CWG		ASOCWG	
	(1)	(2)	(3)	(4)
Constant	157.9438	129.7543	−6.7447	−8.8592
	(378.9964)	(401.4823)	(5.7978)	(5.6160)
m_TIER1	137.3906	82.9938		
	(277.3877)	(304.7645)		
m_TIER1_a			2.7399	2.8806
			(2.0046)	(1.9901)
m_TIER1_t			2.2114	2.6382
			(2.0577)	(2.0048)
m_TIER1_a:m_TIER1_t			−2.2569	−3.1948
			(2.5918)	(2.5581)
c_ABSSIZE	0.0089	0.0062		
	(0.0118)	(0.0124)		
c_SIZE			0.0639	0.3564
			(0.4698)	(0.4567)
c_RELSIZE	106.9373	115.7802	0.0864	−0.2126
	(152.4981)	(157.9742)	(0.7937)	(0.7812)
c_TOEHOLD	−155.7909	−110.0666	2.0692	1.5870
	(308.9771)	(327.4547)	(1.5469)	(1.5353)
c_SHARES	−291.4741	−288.4887	2.9051**	3.5263***
	(264.8151)	(279.1513)	(1.3255)	(1.3058)
c_RUNUP_a	3.0428	4.7537	0.0452	−0.0020
	(12.2613)	(12.7972)	(0.0623)	(0.0613)
c_RUNUP_t	−0.6213	0.6188	−0.0770*	−0.0951**
	(9.1343)	(9.4838)	(0.0458)	(0.0445)
c_SIC	70.1670	43.7746	1.3434	1.0079
	(230.1839)	(245.0380)	(1.1985)	(1.1946)
c_CROSSB	−93.5998	−27.6831	0.7275	0.2416
	(241.6270)	(253.9170)	(1.2680)	(1.2389)
c_ADV_NR_a	19.1899	38.0390	0.0765	−0.0065
	(101.0366)	(105.8757)	(0.5530)	(0.5404)
c_ADV_NR_t	−56.1777	−65.4255	−0.2946	−0.2737
	(107.3622)	(110.0784)	(0.4546)	(0.4479)
c_HOSTILE		−16.1608		−5.8833***
		(375.5403)		(1.7922)
c_CONTESTED		273.4694		−3.7768**
		(329.1751)		(1.6146)
c_UNSOLICITED		−233.1688		3.8468*
		(458.0522)		(2.1619)
c_SOA		174.5858		−2.1925
		(295.1414)		(1.3923)
c_EXIT		−244.0539		0.5371
		(878.7827)		(4.1065)
c_LBO		−861.4776		0.4618
		(728.7576)		(3.4193)
Fixed effects	No	No	No	No
F Statistic	1.57	1.259	0.7477	0.5555
Observations	125	125	125	125
R^2	0.0306	0.0542	0.1065	0.2399
Adjusted R^2	−0.0637	−0.0960	0.0018	0.1024
Residual Std. Error	1179.2430	1197.0130	5.8862	5.5818

*p<0.1; **p<0.05; ***p<0.01

multaneously higher target CAR and ASOCWG, it can not coexist with the significant negative relationship we found between TIER1_a and acquirer CAR. We note that the conflicting patterns observed in Table 11 and in Tables 9 and 10 could also result from using different samples, given the more strict data requirement of CWG and ASOCWG regressions. As our results on examining the relationship between adviser reputation and CWG / ASOCWG are insignificant and inconclusive, we will exclude them from our further analysis.

We briefly note that SHARES and RUNUP_t both gain significance in the ASOCWG regressions. Share payment has a significant positive impact on the acquirer share of the combined wealth gain, which is contradictory to the significant negative effect observed by Golubov et al. (2012). Run-up return of the target is significantly negatively related to ASOCWG, in line with our earlier observations on target CAR. HOSTILE and CONTESTED have significant negative coefficients, possibly resulting from the acquirer offering higher premium in order to ensure deal completion, while the positive coefficient of UNSOLICITED can be interpreted as a better negotiation position of the acquirer given the unpreparedness of the target.

6.3 Premium

Table 12 presents our results on the impact of adviser reputation on deal premium. As the calculation of premium requires the target to be listed, the analysis is performed on the listed target sample. The hypotheses tested are 4a: *Targets hiring at least one Tier 1 adviser receive a higher acquisition premium than targets who do not hire a Tier 1 adviser.* and 4b: *Targets receive a lower acquisition premium if the acquirer hires at least one Tier 1 adviser.* Given the high amount of withdrawn deals, the full sample can be considered somewhat noisy with regards to observed premia. Therefore we present the full sample, together with the completed subsample in Table 12. The regression set up used in regressions (1) and (3) and those used in (2) and (4) follow that of regression (4) and (5) in Table 10, respectively.

First examining Hypothesis 4a, we find that target advisers have a positive relation with deal premia, however, this result is not significant in the full sample at conventional levels. We do, however, find significant relation in the completed deals subsample: targets retaining a Tier1 adviser, receive, on average, a 12.9pp - 15.0pp higher premium than targets who do not hire Tier 1 advisers. These results are significant at the 10% level, and are also economically relevant when compared to the mean (median) premium of 22.8% (16.3%) observed in the completed deals subsample.

Moving on to Hypothesis 4b, we find that TIER1_a has a significant positive relationship with deal premium, contradicting our prediction. According to our results, targets receive a 11.5pp - 13.3pp higher premium, on average, if the acquirer hires at least one Tier 1 adviser. This finding seems to support the deal completion hypothesis, that is, advisers have strong deal completion incentives and focus on closing rather than client wealth gains, thus offering a higher price to ensure a successful outcome. The significant positive effect also persists in the completed sample, where we find that targets receive, on average, a 16.7pp - 17.6pp higher premium (significant at the 5% level), if the acquirer retains a Tier 1 adviser. These findings are also in line with the patterns observed in Section 6.1 where we found that hiring Tier 1 advisers on either side of the deal increases target CAR, which is now explained by the higher premium paid in deals where Tier 1 advisers are retained.

Regarding the interaction term, we observe the same pattern as in the CAR regressions, that is, hiring Tier 1 advisers on both sides of the transaction has a negative incremental effect on premium, just like it did on target CAR in Section 6.1. These results are, however, only significant in the completed deals subsample, where increased complexity and leveled-out negotiation skills eat away 16.5pp - 18.9pp of deal premium, on average. However, despite the increased complexity, Tier 1 advisers still have a positive overall effect on deal premia when hired on both sides, of 13.3pp - 13.8pp, on average, when looking at the completed deals subsample. (Similar to CAR, the regression analysis is also performed separately for the public and private subsamples, as presented in Section A.3.

Similar to the CAR regressions, we briefly examine the coefficients of the control variables, in order to check the logical fit of our model and support its validity. As expected, SIZE is negatively related to deal premium, interpreted as a result of the lower overpayment potential present in larger deals. Similar to target CAR results, both TOEHOLD and SHARES have negative impact on deal premium (significant only in the full sample), supporting Song et al. (2013)'s argument that an existing ownership gives the acquirer a stronger negotiation position and our earlier findings on shareholder preference

Table 12: Adviser reputation and deal premium

This table presents our OLS regression results on the relationship between adviser reputation and deal premium. As the calculation of premium requires the target to be listed, the analysis is performed on the listed target sample only. Given the high amount of withdrawn deals, the full sample can be considered somewhat noisy with regards to observed premia. We therefore also present the completed deals subsample for comparison. The mean (median) deal premium is 26.0% (19.5%) in the full and 22.8% (16.3%) in the completed deals subsample. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	Dependent variable:			
	PREMIUM			
	Full sample		Completed sample	
	(1)	(2)	(3)	(4)
Constant	0.1816	0.2535	0.6098**	0.5038***
	(0.2270)	(0.1608)	(0.2377)	(0.1763)
m_TIER1_a	0.1332**	0.1150**	0.1761**	0.1677**
	(0.0571)	(0.0571)	(0.0689)	(0.0659)
m_TIER1_t	0.0431	0.0489	0.1503*	0.1294*
	(0.0666)	(0.0611)	(0.0847)	(0.0750)
m_TIER1_a:m_TIER1_t	−0.1198	−0.0906	−0.1887**	−0.1645*
	(0.0756)	(0.0783)	(0.0904)	(0.0867)
c_SIZE	−0.0113	−0.0110	−0.0359**	−0.0335**
	(0.0129)	(0.0129)	(0.0151)	(0.0161)
c_TOEHOLD	−0.0825**	−0.0920**	−0.0258	−0.0169
	(0.0414)	(0.0423)	(0.0476)	(0.0475)
c_PUBLIC	0.0653	0.0548	0.0849*	0.0856*
	(0.0493)	(0.0527)	(0.0480)	(0.0471)
c_SHARES	−0.1029**	−0.0931*	−0.0693	−0.0663
	(0.0472)	(0.0502)	(0.0466)	(0.0482)
c_RUNUP	0.0008*	0.0008*	0.0015	0.0023
	(0.0004)	(0.0004)	(0.0024)	(0.0023)
c_SIC	−0.0117	−0.0159	−0.0278	−0.0322
	(0.0322)	(0.0333)	(0.0386)	(0.0389)
c_CROSSB	0.0434	0.0384	−0.0401	−0.0410
	(0.0398)	(0.0400)	(0.0413)	(0.0370)
c_ADV_NR_a	−0.0413**	−0.0411**	−0.0234	−0.0220
	(0.0161)	(0.0162)	(0.0200)	(0.0195)
c_ADV_NR_t	0.0417**	0.0360**	0.0101	0.0065
	(0.0183)	(0.0177)	(0.0157)	(0.0146)
c_HOSTILE	0.0392	0.0192	0.0264	0.0061
	(0.0758)	(0.0791)	(0.1811)	(0.1689)
c_CONTESTED	0.0349	0.0311	−0.1575***	−0.1493***
	(0.0520)	(0.0507)	(0.0570)	(0.0430)
c_UNSOLICITED	0.0248	0.0383	−0.0377	0.0000
	(0.0625)	(0.0646)	(0.0824)	(0.0734)
c_SOA	−0.1015	−0.1027*	−0.1296*	−0.1328**
	(0.0634)	(0.0572)	(0.0671)	(0.0641)
c_EXIT	−0.1646*	−0.1496*	−0.1409*	−0.0882
	(0.0866)	(0.0785)	(0.0763)	(0.0669)
c_LBO	0.2199**	0.1849**	0.3416**	0.2847*
	(0.0914)	(0.0739)	(0.1432)	(0.1533)
c_T6M_NR		0.0180		−0.0041
		(0.0591)		(0.0654)
c_T6M_PREMIUM		−0.0101*		−0.0046
		(0.0060)		(0.0075)
Fixed effects	Year, Country	Country	Year, Country	Country
F Statistic	2.1164***	2.2316***	28.0963***	11.7914***
Observations	407	407	263	263
R^2	0.3001	0.2435	0.2369	0.1782
Adjusted R^2	0.2085	0.1744	0.0701	0.0556
Residual Std. Error	0.3045	0.3110	0.2759	0.2781

*p<0.1; **p<0.05; ***p<0.01

towards cash payments. An interesting observation is that, while Tier 1 advisers have a positive impact on deal premium, the number of acquirer advisers has a negative impact, significant at the 5% level but observed in the full sample only. At the same time, the number of target advisers has a positive impact on deal premia. This might be interpreted as more advisers resulting in stronger negotiation positions for the respective parties.

We also observe results similar to that of the CAR regressions when looking at merger wave proxies: T6M_PREMIUM (last six months premium) has a negative coefficient, significant at the 10% level, while T6M_NR (last six months deal volume) has a positive, although insignificant, impact on deal premia.

6.4 Deal competition

Table 13 presents probit regressions analyzing the impact of Tier 1 advisers on deal completion, examining hypothesis 5 *"Deals, where at least one Tier 1 adviser is hired by either party, are more likely to be completed than deals where no Tier 1 adviser is hired."*. For the purpose of these regressions we narrowed down our full sample to only include deals with deal status *Completed*, *Completed assumed* and *Withdrawn*, as deals that are still pending (with uncertain outcomes) would distort the analysis. As in the combined wealth gain regressions presented in Section 6.2, the combined dummy variable, TIER1 is used, equalling to one for all deals involving at least 1 Target adviser. Despite the dependent variable being deal rather than target / acquirer specific, we decided to conduct the analysis separately for the acquirer and target sample. We do this as the relative size control is not available for the target sample, furthermore, we expect the impact of c_SHARES to depend on c_PUBLIC, which we do not expect to be the case in the target sample. Moreover, competition rates in the two samples are quite different with the average value of the dependent variable c_CLOSED being equal to 0.93 in the listed acquirer and 0.66 in the listed target sample. The density of withdrawn deals is thus substantially higher in the listed target sample.

Based on our earlier findings in the CAR and premium analysis, we predict that the deal completion hypothesis holds, our probit regression on probability of deal completion, however, seems inconclusive. TIER1 shows a positive relationship with the probability of deal completion in regression (2), in the acquirer sample, and in both regressions in the target sample, however, these results are not significant at conventional levels.

Table 13: Adviser reputation and deal completion

This table presents probit regressions analyzing the impact of Tier 1 advisers on deal completion. For the purpose of this analysis we narrowed down the full sample to only include deals with deal status *Completed*, *Completed assumed* and *Withdrawn*. The combined dummy variable TIER1 is equal to one for all deals involving at least 1 Target adviser. As the relative size control is not available for the target sample and we expect the impact of type of payment to depend on c_PUBLIC in the acquirer sample, which we do not expect to be the case in the listed target sample, we analyze acquirer and target sample separately. The average completion rate is equal to 0.93 in the listed acquirer and 0.66 in the listed target sample. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	Dependent variable:			
	c_CLOSED			
	Acquirer sample		Target sample	
	(1)	(2)	(3)	(4)
Constant	2.4751***	1.4839	2.6737***	1.2393
	(0.6721)	(1.0905)	(0.6887)	(1.2007)
m_TIER1	−0.1106	0.0343	0.0771	0.1406
	(0.2052)	(0.2346)	(0.2223)	(0.2708)
c_SIZE	−0.0129	0.0006	−0.1564***	−0.1366*
	(0.0554)	(0.0660)	(0.0577)	(0.0762)
c_RELSIZE	−0.1172**	−0.1770***		
	(0.0536)	(0.0620)		
c_TOEHOLD	0.0807	0.1242	0.1077	0.2544
	(0.2198)	(0.2381)	(0.2037)	(0.2281)
c_PUBLIC	−1.0963***	−1.2671***	0.1950	0.1521
	(0.2485)	(0.2702)	(0.2087)	(0.2221)
c_SHARES	−0.2268	−0.2258	0.2539	0.2030
	(0.2510)	(0.2782)	(0.2142)	(0.2332)
c_PUBLICTRUE:c_SHARES	0.2718	0.2410		
	(0.3263)	(0.3364)		
c_SIC	0.0251	0.1354	−0.0488	−0.1046
	(0.1549)	(0.1879)	(0.1567)	(0.1786)
c_CROSSB	−0.0227	−0.0710	−0.1944	−0.1645
	(0.1558)	(0.1792)	(0.1747)	(0.2005)
c_ADV_NR_a	0.0529	0.0270	0.1195	0.1061
	(0.0871)	(0.0991)	(0.0868)	(0.0927)
c_ADV_NR_t	−0.0847	−0.0919	−0.0164	−0.0055
	(0.0754)	(0.0898)	(0.0624)	(0.0780)
c_HOSTILE	−1.9212***	−1.9692***	−1.4855***	−1.7796***
	(0.4494)	(0.4603)	(0.2634)	(0.3470)
c_CONTESTED	−1.4547***	−1.6348***	−1.2213***	−1.3030***
	(0.2817)	(0.3291)	(0.2056)	(0.2371)
c_UNSOLICITED	−0.9751	−0.8472	−0.8625**	−0.7438*
	(0.5982)	(0.6830)	(0.3642)	(0.4152)
c_SOA	0.3802*	0.0906	0.0156	−0.1136
	(0.2193)	(0.2626)	(0.1876)	(0.3127)
c_EXIT	0.5057*	0.3621	0.3845	0.6012
	(0.2662)	(0.3050)	(0.4390)	(0.4718)
c_LBO	0.4038	0.2684	−0.7233	−0.3995
	(0.3690)	(0.4589)	(0.4659)	(0.5637)
c_ASSET	3.3370***	2.8667***		
	(0.3172)	(0.5588)		
c_REORG	4.4508***	5.0288***		
	(0.3623)	(0.4305)		
Fixed effects	No	Year, Country	No	Year, Country
F Statistic	66.7817***	38.529 ***	6.9529***	12.5686***
Pseudo R^2	0.4417	0.4996	0.2574	0.3305
Observations	1,021	1,021	400	400
Log Likelihood	−170.0016	−152.3661	−190.9026	−172.1089
Akaike Inf. Crit.	380.0031	402.7321	413.8052	434.2179

*p<0.1; **p<0.05; ***p<0.01

Therefore, contrary to our expectation based on CAR and premium results, we do not find empirical evidence for the deal completion hypothesis, and we can neither support nor refute Hypothesis 5.

While we can not identify a relationship between adviser reputation and deal completion, we do find that some control variables have significant and economically relevant impact on the probability of closing. In line with our expectation, larger deals have lower probability of a successful outcome, demonstrated by a significant negative coefficient of SIZE (RELSIZE) in the target (acquirer) sample. SIZE being significant only in the target sample might be attributed to the substantially larger average deal size observed in the target sample (see Table 2), suggesting that the likelihood of closing has an increasingly negative relationship with deal size. Public deals (PUBLIC) in the acquirer sample have a significantly lower probability of completion than deals involving private targets, which, given the wider shareholder base of listed targets, can be seen as a sign of more difficult negotiations and complex deal structuring. We also observe that deals in which the bidder approaches the target without the target actively seeking a transaction, are more likely to fail. The coefficients for HOSTILE and UNSOLICITED are negative, with HOSTILE being significant at the 1% level in both samples. The negative relationship between deal completion probability and the CONTESTED dummy might be a result of multiple bidders pushing up the offer price, eventually making the deal unattractive for acquirers, leading to the falling through in the execution phase.

7 Robustness tests

To support the validity of our results we run robustness tests by varying our analysis settings. We test the robustness of our results with respect to CAR parameters and the relative size cut-off used in defining the acquirer dataset.

7.1 CAR parameters

Announcement CAR is the most commonly applied measure of M&A value creation in existing literature and is also the main input of our analysis. Varying parameters of our CAR calculation is thus an important robustness test to underpin the persistence of our findings. As a standard setting, we use an estimation window of 250 trading days, ending

10 trading days before the event date, combined with an event window of 5 trading days, centered around the announcement date. Estimation windows of the length of 200 to 250 trading days have proven most suited for short term event studies (Bartholdy et al. 2007), and prior papers examining adviser reputation and CAR usually use a 3 to 5 trading days long event window. We therefore vary estimation and event window accordingly, and rerun our regression analyses. For the purpose of comparability, the set of deals is held constant. (The varying estimation and event window lengths would normally affect the sample size through the thickly traded stock condition and winsorization.)

Table A.6 of the appendix shows summary statistics on CAR for varying combinations of estimation and event study lengths. The first setting corresponds to that used throughout our analysis. The figures presented in this table differ from those presented in Table 5 as those presented here are after winsorization, i.e. the final sample used in the regression analysis. Changes in the estimation window appear to only have a very minor impact on CAR statistics, while shortening the event window, leads to a slightly lower average abnormal return. For both samples the three tests performed remain significant at the 1% level for acquirer and target CAR across all tested settings.

In Appendix A.4.1 we present the regression coefficients of the adviser reputation variables across the different event study settings, for all regressions that are based on CAR. Analyzing the impact of adviser dummies on acquirer CAR, the choice of estimation window does not seem to impact our results (see Table A.7). With a shortened event window, however, the coefficient for target advisers becomes positive also in regression settings without fixed effects. As the changed coefficients remain insignificant, they do not alter our findings regarding the validity of our hypotheses. Furthermore our findings on the relation between adviser reputation and target CAR are robust to changes in estimation and event window settings. All previously significant coefficient remain significant and keep the same sign, just the level of significance varies slightly (see Table A.8).

Table A.9 of the appendix presents the adviser reputation coefficients of the robustness test performed on combined wealth gain and acquirer share of combined wealth gain. The coefficients of the TIER1 variable used in the regressions analyzing CWG show no major changes, remaining positive and insignificant despite varying event study settings. The coefficient estimates in the acquirer share of combined wealth gain analysis, on the other hand, do seem to depend on the length of the event window. The relation between

TIER1_a and ASOCWG turns negative and significant in the case of regression (3), which includes country and year fixed effects. This is in line with our findings on CAR, detailed in Section 6.1. Moreover, the coefficients of TIER1_t decrease in magnitude, while the coefficient of the interaction term turns positive, both remain insignificant though. The sensitivity of the results in the analysis of ASOCWG can potentially be ascribed to the small sample size, therefore performing the same analysis on a broader dataset could provide valuable insights.

7.2 Relative size

In determining our listed acquirer sample we impose the condition for deal value to be equal to at least 10% of acquirer's market capitalization 20 trading days before deal announcement. This is to ensure for the acquisition to be sizable enough to trigger a detectable market reaction on deal announcement. As this cut-off is debatable we perform robustness tests, varying the threshold to 5 and 20%. The respective results for regressions based on the acquirer sample are present in Appendix A.4.2.

Table A.10 of the appendix presents the coefficients of adviser dummies of the regression set ups used in Table 9 analyzing the impact of adviser reputation on acquirer CAR, using the different relative size cut offs. With the exception of the interaction term in regression (4) and (5), the signs of the coefficients appear to remain the same for the varying relative size conditions. Increasing the relative size condition to 20% intensifies the significant negative relationship observed earlier between acquirer CAR and TIER1_a, as the coefficient turn significant across all regression variations.

Table A.11 and A.12 of the appendix present the results of the regressions analyzing CWG / ASOCWG and deal completion. For all three dependent variables the adviser dummies remain insignificant, but keep the same sign under varying relative size thresholds, providing no additional evidence on the validity of the respective hypotheses.

8 Conclusion

Motivated by the ambiguous results of existing literature and the lack of comprehensive studies on the European market, we examined top tier advisers' impact on deal performance in European M&A transactions, expecting that their supreme reputation, large market share and above-average compensations are underpinned by superior performance and client service.

Contradicting our expectation, we find that acquirers hiring Tier 1 advisers realize significantly lower announcement returns than other bidders, even after controlling for deal characteristics. We explain this negative impact by showing that Tier 1 advisers offer higher premium when bidding for targets, thus, paradoxically, increasing target wealth gains at the expense of their own clients. We do not observe such controversial patterns when looking at sell-side advisers: targets hiring Tier 1 advisers take home larger deal premia than other targets, and therefore also realize higher announcement returns, consistent with the premium price - premium quality assumption.

The finding that Tier 1 advisers have a negative impact on client returns, when hired on buy-side mandates, seems puzzling. We offer two potential interpretations for this anomaly. Either our results prove right McLaughlin's fears about the misaligned interests of clients and their advisers, or acquirers, indeed, value deal execution abilities more than they value direct merger gains. For example, acquiring strategically important targets might be more important for some companies, than maximizing announcement market reactions. It is also worth noting, that the higher deal premium might (partially) result from Tier 1 advisers constructing more efficient financing structures, that allow for a higher offer price. On the other hand, while our findings on CAR and deal premia seem to support the deal completion hypothesis, we do not find empirical evidence for Tier 1 advisers being more successful in completing deals than other advisers.

It is important to note the limitations of our research. Given the data availability constraints of the Zephyr database, we could only examine the period between 2001 and 2016, which, while it covers the most recent years and trends, represents only a fraction of European M&A history. Furthermore, we focused our analysis on the 15 countries included in the MSCI Europe Index, examining other European countries might yield different results. We also acknowledge that the announcement abnormal return is only one potential measure for value creation, and using different proxies might alter the outcome. Furthermore, given the complexity and inherent interdependency of adviser - client relationships, investment banks might provide value for their clients in ways that are hard or impossible to measure.

With regards to future research, revisiting the better merger and deal completion hypotheses by testing their market-share implications seems a valuable extension to our study, together with examining the question of whether clients 'follow value'. Given the limitations of abnormal returns as value creation proxies, exploring alternative measures, such as long-term returns, could provide interesting insights, while also serving as a cross-check for the persistence and robustness of our findings. Future studies could also add value through examining other types of adviser classifications, such as analysing the deal performance impacts of boutique advisers compared to full-service banks.

References

Alexandridis, G., Fuller, K. P., Terhaar, L. & Travlos, N. G. (2013), 'Deal size, acquisition premia and shareholder gains', *Journal of Corporate Finance* **20**, 1–13.

Alexandridis, G., Petmezas, D. & Travlos, N. G. (2010), 'Gains from mergers and acquisitions around the world: New evidence', *Financial Management* **39**(4), 1671–1695.

Amihud, Y., Lev, B. & Travlos, N. G. (1990), 'Corporate control and the choice of investment financing: The case of corporate acquisitions', *The Journal of Finance* **45**(2), 603–616.

Bao, J. & Edmans, A. (2011), 'Do investment banks matter for m&a returns?', *Review of Financial Studies* p. hhr014.

Bartholdy, J., Olson, D. & Peare, P. (2007), 'Conducting event studies on a small stock exchange', *The European Journal of Finance* **13**(3), 227–252.

Boehmer, E., Masumeci, J. & Poulsen, A. B. (1991), 'Event-study methodology under conditions of event-induced variance', *Journal of Financial Economics* **30**(2), 253–272.

Bowers, H. M. & Miller, R. E. (1990), 'Choice of investment banker and shareholders' wealth of firms involved in acquisitions', *Financial Management* pp. 34–44.

Campbell, C. J., Cowan, A. R. & Salotti, V. (2010), 'Multi-country event-study methods', *Journal of Banking & Finance* **34**(12), 3078–3090.

Chang, S. (1998), 'Takeovers of privately held targets, methods of payment, and bidder returns', *The Journal of Finance* **53**(2), 773–784.

Chen, X., Harford, J. & Li, K. (2007), 'Monitoring: Which institutions matter?', *Journal of Financial Economics* **86**(2), 279–305.

Conn, R. L., Cosh, A., Guest, P. M. & Hughes, A. (2005), 'The impact on uk acquirers of domestic, cross-border, public and private acquisitions', *Journal of Business Finance & Accounting* **32**(5-6), 815–870.

Corrado, C. J. (1989), 'A nonparametric test for abnormal security-price performance in event studies', *Journal of Financial Economics* **23**(2), 385–395.

Cowan, A. R. (1992), 'Nonparametric event study tests', *Review of Quantitative Finance and Accounting* **2**(4), 343–358.

Danbolt, J. (2004), 'Target company cross-border effects in acquisitions into the uk', *European Financial Management* **10**(1), 83–108.

Ertugrul, M. & Krishnan, K. (2011), 'Advisor skill and acquisition performance: Do investment bankers make a difference?'.

Fang, L. H. (2005), 'Investment bank reputation and the price and quality of underwriting services', *The Journal of Finance* **60**(6), 2729–2761.

Ferreira, M. A. & Matos, P. (2008), 'The colors of investors money: The role of institutional investors around the world', *Journal of Financial Economics* **88**(3), 499–533.

Forte, G., Iannotta, G. & Navone, M. (2010), 'The banking relationship's role in the choice of the target's advisor in mergers and acquisitions', *European financial management* **16**(4), 686–701.

Fuller, K., Netter, J. & Stegemoller, M. (2002), 'What do returns to acquiring firms tell us? evidence from firms that make many acquisitions', *The Journal of Finance* **57**(4), 1763–1793.

Goergen, M. & Renneboog, L. (2004), 'Shareholder wealth effects of european domestic and cross-border takeover bids', *European Financial Management* **10**(1), 9–45.

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.

Gorton, G., Kahl, M. & Rosen, R. J. (2009), 'Eat or be eaten: A theory of mergers and firm size', *The Journal of Finance* **64**(3), 1291–1344.

Hunter, W. C. & Jagtiani, J. (2003), 'An analysis of advisor choice, fees, and effort in mergers and acquisitions', *Review of Financial Economics* **12**(1), 65–81.

Hunter, W. C. & Walker, M. B. (1990), 'An empirical examination of investment banking merger fee contracts', *Southern Economic Journal* pp. 1117–1130.

Ince, O. S. & Porter, R. B. (2006), 'Individual equity return data from thomson datastream: Handle with care!', *Journal of Financial Research* **29**(4), 463–479.

Ismail, A. (2010), 'Are good financial advisors really good? the performance of investment banks in the m&a market', *Review of Quantitative Finance and Accounting* **35**(4), 411–429.

Jaffe, J., Pedersen, D. & Voetmann, T. (2013), 'Skill differences in corporate acquisitions', *Journal of Corporate Finance* **23**, 166–181.

Kale, J. R., Kini, O. & Ryan, H. E. (2003), 'Financial advisors and shareholder wealth gains in corporate takeovers', *Journal of Financial and Quantitative Analysis* **38**(03), 475–501.

Kolasinski, A. C. & Kothari, S. (2008), 'Investment banking and analyst objectivity: Evidence from analysts affiliated with mergers and acquisitions advisors', *Journal of Financial and Quantitative Analysis* **43**(04), 817–842.

Martynova, M. & Renneboog, L. (2009), 'What determines the financing decision in corporate takeovers: Cost of capital, agency problems, or the means of payment?', *Journal of Corporate Finance* **15**(3), 290–315.

Maynes, E. & Rumsey, J. (1993), 'Conducting event studies with thinly traded stocks', *Journal of Banking & Finance* **17**(1), 145–157.

McConnell, J. J. & Sibilkov, V. (2016), 'Do investment banks have incentives to help clients make value-creating acquisitions?', *Journal of Applied Corporate Finance* **28**(3), 103–117.

McLaughlin, R. M. (1990), 'Investment-banking contracts in tender offers: An empirical analysis', *Journal of Financial Economics* **28**(1-2), 209–232.

Michel, A., Shaked, I. & Lee, Y.-T. (1991), 'An evaluation of investment banker acquisition advice: the shareholders' perspective', *Financial Management* pp. 40–49.

Moeller, S. B. & Schlingemann, F. P. (2005), 'Global diversification and bidder gains: A comparison between cross-border and domestic acquisitions', *Journal of Banking & Finance* **29**(3), 533–564.

Moeller, S. B., Schlingemann, F. P. & Stulz, R. M. (2004), 'Firm size and the gains from acquisitions', *Journal of financial economics* **73**(2), 201–228.

Rau, P. R. (2000), 'Investment bank market share, contingent fee payments, and the performance of acquiring firms', *Journal of Financial Economics* **56**(2), 293–324.

Rosen, R. J. (2006), 'Merger momentum and investor sentiment: The stock market reaction to merger announcements', *The Journal of Business* **79**(2), 987–1017.

Rossi, S. & Volpin, P. F. (2004), 'Cross-country determinants of mergers and acquisitions', *Journal of Financial Economics* **74**(2), 277–304.

Schwert, G. W. (2000), 'Hostility in takeovers: in the eyes of the beholder?', *The Journal of Finance* **55**(6), 2599–2640.

Sibilkov, V., Straska, M. & Waller, H. G. (2013), 'Do firms use m&a business to pay for analyst coverage?', *Financial Review* **48**(4), 725–751.

Song, W., Wei, J. D. & Zhou, L. (2013), 'The value of boutique financial advisors in mergers and acquisitions', *Journal of Corporate Finance* **20**, 94–114.

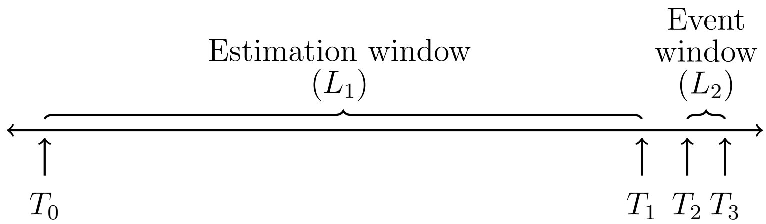
Vancea, M. (2013), 'Mergers and acquisitions waves from the european union perspective', *Annals of Faculty of Economics* **1**(2), 272–283.

A Appendix

A.1 Event-study tests

Campbell et al. (2010) find three tests, one parametric and two non-parametric, to be well specified for multi-country event study settings using trade-to-trade returns. Each test is performed separately for the target and the acquirer dataset. The following notation of estimation / event dates will be used throughout this appendix:

Figure A.1: Event study timeline



$$
\begin{aligned}
T_0 &= \text{Beginnig of estimation window} \\
T_1 &= \text{End of estimation window} \\
T_2 &= \text{Beginnig of event window} \\
T_3 &= \text{End of event window} \\
L_1 &= \text{Length of estimation window} \\
L_2 &= \text{Length of event window}
\end{aligned}
$$

A.1.1 Standardized Cross-Sectional Test

The parametric test performed is the standardized cross-sectional test, representing a variance-change corrected version of the Patell test, developed by Boehmer et al. (1991), which also performs well in the absence of a variance change. It tests the null-hypothesis that CAAR (Cumulative average abnormal return) equals 0. The standardized cross-sectional statistic is:

$$
Z_t = \frac{\sum_{i=1}^{N} SCAR_i(T_2, T_3)}{\sqrt{N} s_{SCAR}} \tag{8}
$$

For the calculation of the test statistic in a multi-day event setting, CAR is transformed to standardized cumulative abnormal return denoted as $SCAR_i(T_2, T_3)$.

$$
SCAR_i(T_2, T_3) = CAR_i(T_2, T_3) / s_{CAR_i(T_2, T_3)} \tag{9}
$$

The estimated standard deviation is calculated as follows:

$$s_{CAR_i(T_2,T_3)} = \left(\frac{1}{M_i - 2} \sum_{k=T_0}^{T_1} u_{ik}^2 \right)^{1/2} \quad \left\{ W_i \left[1 + \frac{W_i}{M_i} + \frac{(\sum_{t=T_2}^{T_3} R_{mt} - W_i \bar{R}_{m\_Est})^2}{\sum_{t=T_0}^{T_1} (R_{mt} - W_i \bar{R}_{m\_Est})^2} \right] \right\}^{1/2} \tag{10}$$

M_i denotes the number of non-missing estimation window returns and W_i the number of non-missing event window returns for security i. $\bar{R}_{m\_Est}$ is defined as the average return of the benchmark index in the estimation window. In line with the calculation of CAR trade-to-trade returns which are corrected for heteroscedasticity introduced in the aggregation of error terms (by dividing the return series by $\sqrt{n}$), are used. The standard deviation of the standardized cumulative abnormal return used in the calculation of the test statistic is defined as follows:

$$s_{SCAR} = \left[\frac{1}{N-1} \sum_{i=1}^{N} \left(SCAR_i(T_2, T_3) - \frac{1}{N} \sum_{i=i}^{N} SCAR_i(T_2, T_3) \right)^2 \right]^{1/2} \tag{11}$$

A.1.2 Generalized sign test

The Generalized sign test as outlined by Cowan (1992) is a non-parametric test, testing the null hypothesis of the fraction of events having a particular CAR sign being equal to the fraction expected to have that sign. The test is performed using an upper tail alternative hypothesis (i.e. the fraction of CAR's having a positive sign being higher than expected). The test statistic is calculated as follows:

$$Z_G = \frac{w - N\hat{p}}{[N\hat{p}(1 - \hat{p})]^{1/2}} \tag{12}$$

w is the number of stocks with a positive cumulative abnormal return in the event window and p is the fraction of cumulative abnormal returns expected to have a positive sign based on the estimation period for N events.

$$\hat{p} = \frac{1}{N} \sum_{i=i}^{N} \frac{1}{M_i} \sum_{t=T_0}^{T_1} S_{it} \tag{13}$$

S_{it} describes the sign of the abnormal return for event i on day t:

$$S_{it} = \begin{cases} 1 & \text{if } u_{it} > 0l \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

A.1.3 Rank test

The second non-parametric test applied is the Corrado (1989) rank test as adapted by Campbell et al. (2010) to accommodate missing observations and a multi-day event window. The null hypothesis of the test is the average rank of the event window abnormal returns being equal to the expected rank. Abnormal returns of each event i are ranked in ascending order across event and estimation window, with the lowest rank being 0. To adjust for missing data each original rank is multiplied by a scaling factor of $(((T_1 - T_0) + (T_3 - T_2))$ / $(1 +$ no. of non-missing returns for event $i))$ and truncating the result to an integer, creating rank k_{it}. The test statistic for the event window is:

$$t_{rank} = \left[\left(\frac{1}{N}\sum_{i=1}^{N}\frac{1}{L_2}\sum_{t=T_3}^{T_2} k_{it}\right) - \bar{k}\right] \Bigg/ \left[\frac{s_k}{\sqrt{L_2}}\right] \tag{15}$$

The expected rank $\bar{k}$ is calculated as empirical mean of the transformed ranks k_{it}:

$$\bar{k} = \frac{1}{(L_1 + L_2)}\left[\left(\sum_{j=T_0}^{T_1}\frac{1}{N_t}\sum_{i=1}^{N_t} k_{it}\right) + \left(\sum_{j=T_2}^{T_3}\frac{1}{N_t}\sum_{i=1}^{N_t} k_{it}\right)\right] \tag{16}$$

The standard deviation s_k is estimated at sample level across estimation and event window:

$$s_k = \left\{\frac{1}{(L_1 + L_2)}\left\{\sum_{j=T_0}^{T_1}\left[\left(\frac{1}{N_t}\sum_{i=1}^{N_t} k_{it}\right) - \bar{k}\right]^2 + \sum_{j=T_2}^{T_3}\left[\left(\frac{1}{N_t}\sum_{i=1}^{N_t} k_{it}\right) - \bar{k}\right]^2\right\}\right\}^{1/2} \tag{17}$$

A.2 CAR distribution across years and countries

Table A.1: Average acquirer CAR and number of deals by country and year

This table presents the average cumulative abnormal announcement return (CAR) in the listed acquirer sample, split by country and year. CAR's are calculated based on the value weighted MSCI Europe, using an event study methodology with a [-260:-10][-2:+2] estimation / event window setting. The figures in brackets represent the number of announced deals in a given country in a given year included in the sample.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Full sample
AT			0.0086		0.0389	0.0192	0.0533		0.0656	0.0181		0.0281					0.0338
			(2)		(1)	(1)	(2)		(3)	(4)		(2)					(15)
BE	-0.0476	-0.0123		-0.0066	0.0384	0.0278	0.0654	-0.0141	0.0742	0.0516	0.0395		0.1951	0.0659	-0.0207	0.0621	0.0255
	(1)	(4)		(5)	(1)	(1)	(4)	(2)	(2)	(2)	(3)		(1)	(1)	(4)	(2)	(33)
CH		-0.0457	0.0626	-0.0594	0.0099	0.0191	0.1004	0.0535	0.0245	0.0241	0.0154	0.0034		0.0737	0.0626	0.0512	0.0336
		(1)	(3)	(2)	(5)	(5)	(3)	(3)	(6)	(1)	(4)	(1)		(2)	(5)	(3)	(44)
DE	-0.032	0.0225	-0.0484	0.0619	0.0082	0.0041	0.0338	0.0257	0.025	0.0354	0.1811	0.0784	-0.0051	0.0288	0.0185	-0.0773	0.0189
	(4)	(5)	(1)	(4)	(16)	(15)	(12)	(5)	(4)	(5)	(1)	(4)	(5)	(7)	(8)	(2)	(98)
DK			0.0205	-0.0144	0.1754	0.0666		-0.0237			0.1116		-0.0218	-0.0077		0.1077	0.0462
			(2)	(2)	(2)	(5)		(2)			(1)		(1)	(2)		(1)	(18)
ES		-0.018	-0.0354	0.008	0.029	0.0268	-0.0365	0.0441	-0.0819	0.0381	0.0041	-0.002	0.0357		0.0289	-0.0251	0.0025
		(6)	(8)	(5)	(8)	(8)	(6)	(4)	(2)	(5)	(3)	(2)	(1)		(3)	(2)	(63)
FI	-0.0608	-0.0582	0.0296	-0.0541	0.0648	0.0465	0.0707	0.0415		0.0731	0.0548	0.0416	0.0497	0.2171	0.0202	0.077	0.0403
	(3)	(4)	(1)	(2)	(9)	(4)	(7)	(2)		(1)	(4)	(1)	(3)	(1)	(4)	(6)	(52)
FR	0.06	0.0769	0.0638	-0.0395	0.0413	-0.0171	0.0217	-0.0035	0.0965	0.0189	0.0304	-0.0255	0.0154	-0.0173	0.0171	-0.0123	0.0199
	(8)	(4)	(7)	(6)	(16)	(7)	(23)	(4)	(4)	(5)	(3)	(4)	(2)	(10)	(5)	(9)	(117)
GB	-0.0219	-0.0207	-0.0349	0.0183	0.0033	0.017	0.0322	-0.0244	0.0376	0.027	-0.0234	0.0333	0.0684	0.0084	0.0263	0.0303	0.0121
	(13)	(18)	(6)	(21)	(28)	(32)	(37)	(11)	(6)	(13)	(15)	(8)	(9)	(23)	(20)	(13)	(273)
IE			-0.0604	0.0111						0.1161	0.1662	-0.0238	0.0257	0.0087	0.0319		0.0293
			(1)	(1)						(2)	(1)	(3)	(3)	(2)	(3)		(16)
IT	-0.1233	-0.0185	-0.0151	0.1108	0.0094	0.0241	0.0239	0.0144	0.039	0.0579	0.0347	-0.0052		0.0097	0.0961	0.0404	0.0176
	(1)	(7)	(9)	(2)	(11)	(4)	(8)	(7)	(3)	(4)	(4)	(4)		(2)	(3)	(5)	(74)
NL	0.0399	0.0305	0.0489	-0.0192	0.0039	-0.0469	-0.017	-0.0038	0.0157	0.0685	-0.0014	0.0135	0.1529	0.0186	-0.0264	-0.1931	0.0099
	(2)	(3)	(1)	(3)	(5)	(1)	(8)	(4)	(1)	(3)	(2)	(3)	(3)	(4)	(4)	(1)	(48)
NO	0.037	0.002	0.0099	-0.029	0.1532	0.1233	-0.0067	0.0606	0.0848	0.0282			0.0752	0.136	0.0634	0.1166	0.0592
	(3)	(1)	(2)	(3)	(2)	(5)	(6)	(2)	(1)	(1)			(3)	(2)	(1)	(3)	(35)
PT				-0.0322			0.0448						0.0231				0.0119
				(1)			(1)						(1)				(3)
SE	-0.0467	0.0255	0.0468	0.0163	0.0383	-0.0377	0.0027	0.036	0.0372	0.0305	0.0587	0.0466	0.0832	0.0565	-0.0065	0.0274	0.0257
	(7)	(2)	(10)	(9)	(16)	(9)	(17)	(7)	(7)	(11)	(13)	(4)	(5)	(10)	(6)	(15)	(148)
Full sample	-0.01	-0.0068	0.0099	0.0053	0.0268	0.0174	0.0235	0.0123	0.0389	0.0372	0.028	0.0197	0.0589	0.024	0.0221	0.0274	0.0208
	(42)	(55)	(53)	(66)	(120)	(97)	(134)	(53)	(39)	(57)	(54)	(36)	(37)	(66)	(66)	(62)	(1037)

Table A.2: Average target CAR and number of deals by country and year

This table presents the average cumulative abnormal announcement return (CAR) in the listed target sample, split by country and year. CAR's are calculated based on the value weighted MSCI Europe, using an event study methodology with a [-260:-10][-2:+2] estimation / event window setting. The figures in brackets represent the number of announced deals in a given country in a given year included in the sample.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Full sample
AT					-0.084				0.1087	0.149							0.0706
					(1)				(2)	(1)							(4)
BE					0.1125		0.1023	0.1972		0.0405	0.0344		0.0134		-7e-04		0.0892
					(5)		(2)	(2)		(1)	(1)		(1)		(2)		(14)
CH			0.2252		0.0791	0.0502	0.064	0.046	0.1866		0.1482			0.2553	0.0718	0.0863	0.1107
			(2)		(3)	(4)	(3)	(2)	(1)		(2)			(2)	(1)	(1)	(21)
DE	0.0764	0.1415	-0.0143		0.1228	0.0819	0.0496	0.1514	0.2394	0.0801	0.1405	0.1024	0.0232	-0.0779	0.0844	0.057	0.1092
	(3)	(5)	(1)		(3)	(7)	(4)	(7)	(4)	(1)	(7)	(3)	(2)	(1)	(5)	(1)	(54)
DK		0.1564	0.3167					0.1055	0.0853			0.3492		0.0168			0.1767
		(1)	(1)					(3)	(1)			(2)		(1)			(9)
ES	0.1656	0.016	-0.0429		0.1006	0.1602	0.0174		-0.1157	-0.0257		0.212	0.1376			0.1842	0.0764
	(2)	(2)	(4)		(1)	(6)	(2)		(1)	(1)		(1)	(1)			(1)	(22)
FI		0.1222							0.2375				-0.0175	0.1186	0.1152	0.1216	0.1163
		(1)							(1)				(1)	(1)	(1)	(1)	(6)
FR		-0.0175	-0.0817	0.0428	0.0372	0.0195	0.0159	0.34	0.0082			0.0682		0.0249	0.0303	0.0871	0.0459
		(2)	(1)	(2)	(2)	(2)	(8)	(2)	(1)			(1)		(5)	(4)	(4)	(34)
GB	0.1017	0.1836	0.1981	0.1371	0.1633	0.1193	0.11	0.1256	0.0492	0.1143	0.0822	0.1927	0.1628	0.1648	0.1032	0.1431	0.1301
	(7)	(6)	(5)	(7)	(12)	(26)	(16)	(11)	(6)	(4)	(4)	(5)	(3)	(4)	(9)	(13)	(138)
IE							0.1257					0.2123	0.066	0.2269	-0.0368	0.3573	0.1163
							(1)					(1)	(3)	(1)	(2)	(1)	(9)
IT		0.1554			-0.0277		0.1106					0.2123			0.4207		0.1158
		(1)			(3)		(2)					(1)			(1)		(8)
NL		0.2448	-0.0665	0.0515	-0.0363	0.0103	-0.029	0.0661		0.0054				0.1261	0.0721	0.1217	0.0526
		(2)	(1)	(1)	(2)	(2)	(6)	(4)		(2)				(4)	(5)	(2)	(31)
NO			0.2513		0.065	0.0244	0.0586	0.0116	-0.0075			-0.0055	0.0448			0.3791	0.0641
			(1)		(1)	(1)	(4)	(4)	(2)			(1)	(1)			(1)	(16)
PT						0.1881	-0.033		0.1988			0.1143		0.1861	0.3072		0.158
						(2)	(1)		(1)			(2)		(1)	(1)		(8)
SE		0.2411	0.0856	-0.0127	-0.0263	0.2111	0.1398	0.068	0.1383	0.0614	0.1278		0.2245	0.1042	0.1436	0.4021	0.1559
		(2)	(2)	(1)	(1)	(5)	(1)	(4)	(3)	(2)	(1)		(2)	(3)	(3)	(3)	(33)
Full sample	0.106	0.146	0.1026	0.0986	0.0912	0.1155	0.0606	0.1156	0.1074	0.0696	0.1181	0.1704	0.0972	0.1123	0.0913	0.173	0.1088
	(12)	(22)	(18)	(11)	(34)	(55)	(50)	(39)	(23)	(12)	(15)	(17)	(14)	(23)	(34)	(28)	(407)

A.3 Public and private subsample regressions

Table A.3: Public and private subsample regressions - Acquirer CAR

This table presents our OLS regression results on the relationship between adviser reputation and acquirer CAR, presented separately for the public and private subsamples. In order to decrease the impact of noise and make CAR measurement more reliable, we excluded transactions with a deal value representing less than 10% of the acquirer's market capitalization. Both completed and non-completed deals are included in the analysis. Mean (median) acquirer CAR in the public and private samples is -0.7% (-0.4%) and 3.3% (2.5%), respectively. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	Dependent variable:					
	CAR					
	Public subsample: Listed targets			Private subsample: Unlisted targets		
	(1)	(2)	(3)	(4)	(5)	(5)
Constant	−0.0162	−0.0392	−0.0296	0.0220	0.0108	0.0521*
	(0.0339)	(0.0514)	(0.0386)	(0.0208)	(0.0336)	(0.0303)
m_TIER1_a	−0.0113	−0.0212	−0.0213	−0.0167*	−0.0116	−0.0160*
	(0.0122)	(0.0142)	(0.0131)	(0.0094)	(0.0093)	(0.0096)
m_TIER1_t	−0.0003	−0.0051	0.0000	0.0011	0.0118	0.0060
	(0.0149)	(0.0156)	(0.0149)	(0.0172)	(0.0192)	(0.0188)
m_TIER1_a:m_TIER1_t	0.0080	0.0210	0.0167	0.0028	−0.0073	0.0024
	(0.0191)	(0.0203)	(0.0197)	(0.0186)	(0.0212)	(0.0205)
c_SIZE	0.0025	0.0017	0.0019	0.0004	0.0002	−0.0001
	(0.0029)	(0.0032)	(0.0029)	(0.0019)	(0.0019)	(0.0019)
c_RELSIZE	−0.0024	−0.0031	−0.0033	0.0120***	0.0105***	0.0113***
	(0.0061)	(0.0071)	(0.0069)	(0.0036)	(0.0035)	(0.0035)
c_TOEHOLD	0.0017	−0.0032	−0.0009	−0.0265*	−0.0315**	−0.0256*
	(0.0077)	(0.0085)	(0.0080)	(0.0145)	(0.0139)	(0.0147)
c_SHARES	−0.0201**	−0.0178*	−0.0189**	0.0028	0.0032	0.0026
	(0.0084)	(0.0093)	(0.0087)	(0.0060)	(0.0061)	(0.0061)
c_RUNUP	−0.0004	−0.0003	−0.0005	0.0001	0.0001	0.0001
	(0.0006)	(0.0005)	(0.0006)	(0.0001)	(0.0001)	(0.0001)
c_SIC	0.0024	−0.0005	0.0028	0.0067	0.0077	0.0085
	(0.0076)	(0.0086)	(0.0077)	(0.0060)	(0.0060)	(0.0060)
c_CROSSB	0.0029	0.0032	0.0018	−0.0059	−0.0130**	−0.0125*
	(0.0092)	(0.0090)	(0.0087)	(0.0059)	(0.0064)	(0.0064)
c_ADV_NR_a	−0.0019	−0.0040	−0.0036	0.0040	0.0034	0.0047
	(0.0040)	(0.0044)	(0.0040)	(0.0037)	(0.0039)	(0.0039)
c_ADV_NR_t	−0.0021	−0.0020	−0.0027	−0.0096	−0.0072	−0.0068
	(0.0034)	(0.0038)	(0.0035)	(0.0081)	(0.0081)	(0.0081)
c_HOSTILE	−0.0318***	−0.0287**	−0.0309**			
	(0.0118)	(0.0129)	(0.0126)			
c_CONTESTED	−0.0100	−0.0078	−0.0072	0.0033	0.0120	0.0084
	(0.0107)	(0.0110)	(0.0107)	(0.0213)	(0.0282)	(0.0259)
c_UNSOLICITED	0.0039	0.0185	0.0180	−0.0763***	−0.0758***	−0.0646***
	(0.0136)	(0.0149)	(0.0134)	(0.0146)	(0.0195)	(0.0168)
c_SOA	0.0042	−0.0013	0.0015	−0.0052	0.0022	0.0025
	(0.0098)	(0.0124)	(0.0113)	(0.0336)	(0.0416)	(0.0375)
c_EXIT	0.0138	0.0116	0.0168	−0.0007	−0.0001	−0.0001
	(0.0146)	(0.0170)	(0.0156)	(0.0074)	(0.0073)	(0.0076)
c_LBO	−0.0027	0.0055	−0.0008	0.0175	0.0028	0.0014
	(0.0467)	(0.0437)	(0.0391)	(0.0175)	(0.0175)	(0.0154)
c_ASSET	0.1268**	0.0866*	0.0933*	0.0312	0.0375**	0.0380**
	(0.0517)	(0.0510)	(0.0502)	(0.0195)	(0.0188)	(0.0181)
c_REORG	−0.0088	0.0033	0.0003	−0.1135***	−0.1124***	−0.1075***
	(0.0159)	(0.0220)	(0.0200)	(0.0121)	(0.0167)	(0.0172)
c_T6M_NR			0.0340**			−0.0226**
			(0.0139)			(0.0113)
c_T6M_CAR			0.6433			0.9407***
			(0.4216)			(0.3498)
Fixed effects	No	Year, Country	Country	No	Year, Country	Country
F Statistic	91.1416***	47.0626***	56.3499***	39.2361***	8.5384***	8.1185***
Observations	312	312	312	725	725	725
R^2	0.0805	0.2020	0.1817	0.0556	0.1293	0.1027
Adjusted R^2	0.0173	0.0528	0.0746	0.0302	0.0675	0.0571
Residual Std. Error	0.0627	0.0615	0.0608	0.0764	0.0749	0.0753

*p<0.1; **p<0.05; ***p<0.01

Table A.4: Public and private subsample regressions - Target CAR

This table presents our OLS regression results on the relationship between adviser reputation and target CAR, presented separately for the public and private subsamples. Both completed and non-completed deals are included in the analysis. Mean (median) target CAR in the public and private sample is 9.9% (7.5%) and 11.8% (7.5%), respectively. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	Dependent variable:					
	CAR					
	Public subsample: Listed acquirers			Private subsample: Unlisted acquirers		
	(1)	(2)	(3)	(4)	(5)	(5)
Constant	0.2680***	0.0365	0.1425	0.3640***	0.3571**	0.3097**
	(0.0784)	(0.1313)	(0.1238)	(0.1026)	(0.1764)	(0.1536)
m_TIER1_a	0.0551*	0.0623*	0.0486	0.0517	0.0630*	0.0590*
	(0.0307)	(0.0361)	(0.0322)	(0.0342)	(0.0359)	(0.0346)
m_TIER1_t	0.1131***	0.1324***	0.1206***	0.0463	0.0666	0.0457
	(0.0378)	(0.0492)	(0.0424)	(0.0393)	(0.0462)	(0.0428)
m_TIER1_a:m_TIER1_t	−0.0915**	−0.1136**	−0.0902*	−0.0363	−0.0178	−0.0311
	(0.0453)	(0.0528)	(0.0481)	(0.0440)	(0.0488)	(0.0456)
c_SIZE	−0.0163**	−0.0172**	−0.0148*	−0.0199**	−0.0235**	−0.0184*
	(0.0069)	(0.0084)	(0.0078)	(0.0088)	(0.0100)	(0.0095)
c_TOEHOLD	−0.0522**	−0.0394	−0.0405	−0.0355	−0.0334	−0.0353
	(0.0238)	(0.0272)	(0.0257)	(0.0232)	(0.0229)	(0.0219)
c_SHARES	−0.0269	−0.0372	−0.0397	−0.0677**	−0.0408	−0.0491
	(0.0223)	(0.0256)	(0.0250)	(0.0281)	(0.0406)	(0.0310)
c_RUNUP	0.0003	0.0003	0.0002	0.0005***	0.0005***	0.0005***
	(0.0006)	(0.0008)	(0.0006)	(0.0002)	(0.0002)	(0.0002)
c_SIC	0.0409**	0.0634***	0.0595***	0.0057	0.0173	0.0058
	(0.0187)	(0.0204)	(0.0195)	(0.0222)	(0.0233)	(0.0230)
c_CROSSB	0.0200	0.0291	0.0226	0.0004	−0.0107	−0.0098
	(0.0211)	(0.0245)	(0.0246)	(0.0237)	(0.0249)	(0.0243)
c_ADV_NR_a	−0.0080	−0.0077	−0.0100	−0.0133	−0.0239**	−0.0189**
	(0.0095)	(0.0105)	(0.0102)	(0.0096)	(0.0108)	(0.0094)
c_ADV_NR_t	−0.0017	0.0017	0.0030	−0.0067	−0.0075	−0.0052
	(0.0076)	(0.0080)	(0.0076)	(0.0066)	(0.0079)	(0.0067)
c_HOSTILE	−0.0160	−0.0453	−0.0527	0.0196	−0.0022	−0.0072
	(0.0295)	(0.0339)	(0.0339)	(0.0276)	(0.0362)	(0.0340)
c_CONTESTED	0.0587*	0.0696*	0.0672*	−0.0170	−0.0283	−0.0245
	(0.0302)	(0.0386)	(0.0358)	(0.0253)	(0.0284)	(0.0281)
c_UNSOLICITED	0.0321	0.0322	0.0194	0.0235	0.0517	0.0457
	(0.0358)	(0.0432)	(0.0378)	(0.0367)	(0.0519)	(0.0438)
c_SOA	−0.0210	−0.0749*	−0.0709*	0.0412*	0.0576*	0.0523*
	(0.0227)	(0.0444)	(0.0408)	(0.0245)	(0.0314)	(0.0300)
c_EXIT	0.0041	−0.0136	0.0077	0.0068	0.0126	0.0347
	(0.0488)	(0.0626)	(0.0559)	(0.0564)	(0.0571)	(0.0526)
c_LBO	0.1882**	0.1899**	0.1563**	0.1596***	0.1789**	0.1833***
	(0.0738)	(0.0836)	(0.0736)	(0.0506)	(0.0695)	(0.0595)
c_T6M_NR			−0.0919***			0.0286
			(0.0336)			(0.0444)
c_T6M_CAR			0.0452			−0.0470
			(0.2157)			(0.1863)
Fixed effects	No	Year, Country	Country	No	Year, Country	Country
F Statistic	2.1574***	2.0833***	2.2928***	3.7296***	2.1272***	2.7927***
Observations	201	201	201	206	206	206
R^2	0.2112	0.3479	0.3125	0.1799	0.3483	0.2577
Adjusted R^2	0.1379	0.1531	0.1766	0.1057	0.1597	0.1153
Residual Std. Error	0.1256	0.1245	0.1228	0.1357	0.1315	0.1350

*p<0.1; **p<0.05; ***p<0.01

Table A.5: Private and public subsample regressions - Deal premium

This table presents our OLS regression results on the relationship between adviser reputation and deal premium, presented separately for the public and private subsamples. As the calculation of premium requires the target to be listed, the analysis is performed on the listed target sample only. The mean (median) deal premium is 26.4% (18.3%) in the public and 25.6% (20.3%) in the private subsample. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	Dependent variable:			
	PREMIUM			
	Public sample		Private sample	
	(1)	(2)	(3)	(4)
Constant	0.2283	0.1929	−0.0297	0.3729
	(0.3796)	(0.3447)	(0.3672)	(0.3011)
m_TIER1_a	0.1545*	0.1299	0.1054	0.1151
	(0.0924)	(0.0908)	(0.0777)	(0.0795)
m_TIER1_t	0.1776*	0.1393	−0.0284	0.0122
	(0.0980)	(0.0929)	(0.0830)	(0.0816)
m_TIER1_a:m_TIER1_t	−0.2942**	−0.2602**	0.0427	0.0539
	(0.1178)	(0.1153)	(0.0966)	(0.0977)
c_SIZE	−0.0395*	−0.0272	0.0039	−0.0099
	(0.0210)	(0.0204)	(0.0199)	(0.0194)
c_TOEHOLD	−0.0094	0.0112	−0.0869	−0.1283**
	(0.0661)	(0.0649)	(0.0576)	(0.0561)
c_SHARES	−0.1093*	−0.0793	−0.0045	0.0029
	(0.0592)	(0.0578)	(0.0995)	(0.0911)
c_RUNUP	0.0011	0.0013	0.0005	0.0004
	(0.0022)	(0.0020)	(0.0006)	(0.0006)
c_SIC	0.0128	0.0042	−0.0605	−0.0396
	(0.0535)	(0.0522)	(0.0472)	(0.0474)
c_CROSSB	0.0570	0.0439	0.0492	0.0572
	(0.0592)	(0.0582)	(0.0573)	(0.0572)
c_ADV_NR_a	−0.0334	−0.0400	−0.0254	−0.0253
	(0.0277)	(0.0266)	(0.0262)	(0.0258)
c_ADV_NR_t	0.0985***	0.0954***	−0.0291	−0.0262
	(0.0233)	(0.0222)	(0.0202)	(0.0197)
c_HOSTILE	−0.0504	−0.0934	0.0828	0.0916
	(0.0853)	(0.0828)	(0.0835)	(0.0828)
c_CONTESTED	−0.0433	−0.0078	0.0108	0.0134
	(0.0756)	(0.0733)	(0.0591)	(0.0571)
c_UNSOLICITED	0.0794	0.0410	−0.0497	−0.0284
	(0.0968)	(0.0915)	(0.0946)	(0.0976)
c_SOA	−0.2483**	−0.2421***	0.0265	0.0368
	(0.0965)	(0.0840)	(0.0804)	(0.0771)
c_EXIT	−0.2769*	−0.1706	−0.1157	−0.1892*
	(0.1594)	(0.1551)	(0.1212)	(0.1140)
c_LBO	0.3409	0.1726	0.1533	0.1679
	(0.2182)	(0.1728)	(0.1213)	(0.1102)
c_T6M_NR		0.0283		−0.0640
		(0.0933)		(0.0903)
c_T6M_PREMIUM		−0.0101		−0.0018
		(0.0134)		(0.0140)
Fixed effects	Year, Country	Country	Year, Country	Country
F Statistic	2.6940***	3.1403***	2.1605***	2.1762***
Observations	201	201	206	206
R^2	0.4459	0.3829	0.3846	0.2945
Adjusted R^2	0.2804	0.2610	0.2066	0.1592
Residual Std. Error	0.3126	0.3168	0.2809	0.2892

*p<0.1; **p<0.05; ***p<0.01

A.4 Robustness tests

A.4.1 Event study settings

Table A.6: CAR statistics for varying Estimation and Event window settings

This table presents CAR results for different estimation and event window settings. The figures shown for the base setting used throughout this thesis [-260:-10][-2:+2] differ from the figures presented in Table 5, as those are pre-winsorization figures, while the figures in this table are on the final sample used in the regression analysis. For details on the calculation of the presented test statistics see Section A.1.

		[-260:-10][-2:+2]		[-260:-10][-1:+1]		[-210:-10][-1:+1]		[-210:-10][-2:+2]	
	Test statistic	Acquirer	Target	Acquirer	Target	Acquirer	Target	Acquirer	Target
Sample size		1037	407	1037	407	1037	407	1037	407
Average CAR		0.0208	0.1088	0.0192	0.1031	0.0192	0.1026	0.0208	0.1080
Median CAR		0.0150	0.0753	0.0141	0.0656	0.0142	0.0654	0.0156	0.0738
Minimum CAR		−0.2017	−0.1917	−0.2346	−0.6544	−0.2322	−0.6299	−0.2034	−0.2224
Maximum CAR		0.2865	0.6677	0.3493	0.6339	0.3547	0.6328	0.2916	0.6653
Standard deviation CAR		0.0757	0.1397	0.0695	0.1378	0.0697	0.1378	0.0754	0.1403
Standardized cross sectional test	Z	8.8693***	15.5103***	8.9033***	14.8407***	8.8989***	14.8029***	8.9384***	15.3242***
Generalized sign test	Z	8.4736***	12.5455***	8.0398***	13.3393***	8.1852***	13.6610***	8.3095***	12.1713***
Rank test	t	6.5314***	8.3170***	7.6179***	9.4169***	7.2934***	8.7870***	6.3092***	7.6979***

*p<0.1; **p<0.05; ***p<0.01

Table A.7: Robustness tests - Event study settings - Acquirer CAR

This table shows the Tier1 coefficients of OLS regressions analyzing the relationship between adviser reputation and acquirer CAR under varying settings for estimation and event window. The regression set-ups correspond to those used in Table 9. Regression (1) does not include controls beyond the variables presented here, Regression (2) further includes controls for deal specific characteristics, to which deal type dummies are added in Regression (3). Regression (4) additionally includes year and country fixed effects, while Regression (5) includes country fixed effects and merger wave proxies. To achieve comparability the deal sample included in the analysis is held constant for the robustness analysis, rather than applying the filtering step described in Section 4.1.1 to the different event study settings. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	CAR - Standard sample				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	−0.0146**	−0.0129*	−0.0135*	−0.0085	−0.0109
	(0.0063)	(0.0073)	(0.0073)	(0.0072)	(0.0073)
m_TIER1_t	−0.0308***	−0.0035	−0.0018	0.0088	0.0068
	(0.0095)	(0.0109)	(0.0110)	(0.0114)	(0.0112)
m_TIER1_a:m_TIER1_t	0.0119	0.0082	0.0069	−0.0003	0.0017
	(0.0120)	(0.0124)	(0.0125)	(0.0129)	(0.0126)
Observations	1,037	1,037	1,037	1,037	1,037
	CAR - Robustness - Estimation window [-260:-10], Event window [-1,+1]				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	−0.0149**	−0.0120*	−0.0122*	−0.0083	−0.0110
	(0.0059)	(0.0069)	(0.0069)	(0.0068)	(0.0069)
m_TIER1_t	−0.0258***	0.0040	0.0035	0.0110	0.0090
	(0.0084)	(0.0095)	(0.0094)	(0.0097)	(0.0096)
m_TIER1_a:m_TIER1_t	0.0094	0.0063	0.0079	0.0032	0.0049
	(0.0108)	(0.0111)	(0.0111)	(0.0114)	(0.0113)
Observations	1,037	1,037	1,037	1,037	1,037
	CAR - Robustness - Estimation window [-210:-10], Event window [-1,+1]				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	−0.0151**	−0.0127*	−0.0128*	−0.0090	−0.0118*
	(0.0059)	(0.0070)	(0.0070)	(0.0069)	(0.0070)
m_TIER1_t	−0.0262***	0.0032	0.0027	0.0101	0.0080
	(0.0084)	(0.0095)	(0.0094)	(0.0097)	(0.0095)
m_TIER1_a:m_TIER1_t	0.0100	0.0073	0.0088	0.0041	0.0059
	(0.0108)	(0.0111)	(0.0111)	(0.0114)	(0.0113)
Observations	1,037	1,037	1,037	1,037	1,037
	CAR - Robustness - Estimation window [-210:-10], Event window [-2,+2]				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	−0.0145**	−0.0133*	−0.0139*	−0.0088	−0.0114
	(0.0063)	(0.0073)	(0.0073)	(0.0072)	(0.0073)
m_TIER1_t	−0.0307***	−0.0037	−0.0018	0.0087	0.0063
	(0.0095)	(0.0108)	(0.0109)	(0.0113)	(0.0111)
m_TIER1_a:m_TIER1_t	0.0117	0.0082	0.0065	−0.0008	0.0015
	(0.0119)	(0.0123)	(0.0124)	(0.0128)	(0.0126)
Observations	1,037	1,037	1,037	1,037	1,037

*p<0.1; **p<0.05; ***p<0.01

Table A.8: Robustness tests - Event study settings - Target CAR

This table shows the Tier1 coefficients of OLS regressions analyzing the relationship between adviser reputation and target CAR under varying settings for estimation and event window. The regression set-ups correspond to those used in Table 10. Regression (1) does not include controls beyond the variables presented here, Regression (2) further includes controls for deal specific characteristics, to which deal type dummies are added in Regression (3). Regression (4) additionally includes year and country fixed effects, while Regression (5) includes country fixed effects and merger wave proxies. To achieve comparability the deal sample included in the analysis is held constant for the robustness analysis, rather than applying the filtering step described in Section 4.1.1 to the different event study settings. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	CAR - Standard sample				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	0.0302	0.0466**	0.0504**	0.0584**	0.0514**
	(0.0204)	(0.0221)	(0.0229)	(0.0246)	(0.0233)
m_TIER1_t	0.0409*	0.0774***	0.0748***	0.0828***	0.0754***
	(0.0235)	(0.0278)	(0.0268)	(0.0306)	(0.0281)
m_TIER1_a:m_TIER1_t	−0.0833***	−0.0732**	−0.0675**	−0.0723**	−0.0643**
	(0.0308)	(0.0334)	(0.0318)	(0.0346)	(0.0323)
Observations	407	407	407	407	407
	CAR - Robustness - Estimation window [-260:-10], Event window [-1,+1]				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	0.0228	0.0406*	0.0478**	0.0573**	0.0511**
	(0.0201)	(0.0218)	(0.0230)	(0.0249)	(0.0237)
m_TIER1_t	0.0317	0.0670***	0.0664***	0.0763***	0.0701***
	(0.0221)	(0.0256)	(0.0246)	(0.0286)	(0.0263)
m_TIER1_a:m_TIER1_t	−0.0746**	−0.0633**	−0.0598**	−0.0660**	−0.0585*
	(0.0297)	(0.0320)	(0.0305)	(0.0330)	(0.0309)
Observations	407	407	407	407	407
	CAR - Robustness - Estimation window [-210:-10], Event window [-1,+1]				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	0.0215	0.0374*	0.0452**	0.0545**	0.0484**
	(0.0201)	(0.0220)	(0.0231)	(0.0248)	(0.0235)
m_TIER1_t	0.0305	0.0641**	0.0638**	0.0734**	0.0672**
	(0.0223)	(0.0261)	(0.0250)	(0.0286)	(0.0266)
m_TIER1_a:m_TIER1_t	−0.0719**	−0.0594*	−0.0561*	−0.0624*	−0.0546*
	(0.0298)	(0.0323)	(0.0307)	(0.0330)	(0.0309)
Observations	407	407	407	407	407
	CAR - Robustness - Estimation window [-210:-10], Event window [-2,+2]				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	0.0285	0.0439*	0.0469**	0.0547**	0.0475**
	(0.0205)	(0.0225)	(0.0232)	(0.0249)	(0.0236)
m_TIER1_t	0.0389	0.0731**	0.0701**	0.0783**	0.0714**
	(0.0240)	(0.0288)	(0.0277)	(0.0311)	(0.0291)
m_TIER1_a:m_TIER1_t	−0.0792**	−0.0663*	−0.0592*	−0.0648*	−0.0557*
	(0.0312)	(0.0341)	(0.0325)	(0.0351)	(0.0329)
Observations	407	407	407	407	407

*p<0.1; **p<0.05; ***p<0.01

Table A.9: Robustness tests - Event study settings - CWG / ASOCWG

This table shows the Tier1 coefficients of OLS regressions analyzing the relationship between adviser reputation and combined wealth gain (Regression (1) and (2)), and acquirer share of combined wealth gain (Regression (3) and (4)) respectively. For the purpose of robustness testing the settings of estimation and event window are varied. The regression set-ups correspond to those used in Table 11. In addition to the presented coefficients Regression (1) and (3) include deal specific characteristics and Regression (2) and (4) further include deal type dummies. Given the small sample size, no fixed effects are included in order to avoid overspecification issues. To achieve comparability the deal sample included in the analysis is held constant for the robustness analysis, rather than applying the filtering step described in Section 4.1.1 to the different event study settings. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	CWG & ASOCWG - Standard sample			
	(1)	(2)	(3)	(4)
m_TIER1	137.3906	82.9938		
	(277.3877)	(304.7645)		
m_TIER1_a			2.7399	2.8806
			(2.0046)	(1.9901)
m_TIER1_t			2.2114	2.6382
			(2.0577)	(2.0048)
m_TIER1_a:m_TIER1_t			−2.2569	−3.1948
			(2.5918)	(2.5581)
Observations	125	125	125	125
	CWG & ASOCWG - Robustness - Estimation window [-260:-10], Event window [-1,+1]			
	(1)	(2)	(3)	(4)
m_TIER1	180.3891	121.2432		
	(296.0723)	(317.8150)		
m_TIER1_a			−2.5801*	−2.4488
			(1.4503)	(1.5477)
m_TIER1_t			0.4419	0.5579
			(1.4961)	(1.5630)
m_TIER1_a:m_TIER1_t			3.0237	2.8779
			(1.8913)	(2.0128)
Observations	125	125	125	125
	CWG & ASOCWG - Robustness - Estimation window [-210:-10], Event window [-1,+1]			
	(1)	(2)	(3)	(4)
m_TIER1	179.8828	118.4826		
	(294.4855)	(316.1566)		
m_TIER1_a			−1.5025*	−1.1808
			(0.7979)	(0.8251)
m_TIER1_t			0.1416	0.5158
			(0.8218)	(0.8341)
m_TIER1_a:m_TIER1_t			1.4767	0.8713
			(1.0327)	(1.0651)
Observations	125	125	125	125
	CWG & ASOCWG - Robustness - Estimation window [-210:-10], Event window [-2,+2]			
	(1)	(2)	(3)	(4)
m_TIER1	129.1387	74.1422		
	(276.7425)	(302.8785)		
m_TIER1_a			6.3635	4.4224
			(5.6188)	(5.9007)
m_TIER1_t			2.0969	1.3581
			(5.7871)	(5.9650)
m_TIER1_a:m_TIER1_t			−7.4897	−6.7867
			(7.2726)	(7.6174)
Observations	125	125	125	125

*p<0.1; **p<0.05; ***p<0.01

A.4.2 Relative size

Table A.10: Robustness tests - Relative size cut-off - Acquirer CAR

This table shows the Tier1 coefficients of OLS regressions analyzing the relationship between adviser reputation and acquirer CAR under varying relative size thresholds. The regression set-ups correspond to those used in Table 9. Regression (1) does not include controls beyond the variables presented here, Regression (2) further includes controls for deal specific characteristics, to which deal type dummies are added in Regression (3). Regression (4) additionally includes year and country fixed effects, while Regression (5) includes country fixed effects and merger wave proxies. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	CAR - Standard sample				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	−0.0146**	−0.0129*	−0.0135*	−0.0085	−0.0109
	(0.0063)	(0.0073)	(0.0073)	(0.0072)	(0.0073)
m_TIER1_t	−0.0308***	−0.0035	−0.0018	0.0088	0.0068
	(0.0095)	(0.0109)	(0.0110)	(0.0114)	(0.0112)
m_TIER1_a:m_TIER1_t	0.0119	0.0082	0.0069	−0.0003	0.0017
	(0.0120)	(0.0124)	(0.0125)	(0.0129)	(0.0126)
Observations	1,037	1,037	1,037	1,037	1,037
	CAR - Robustness - Relative size 5%				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	−0.0065	−0.0061	−0.0065	−0.0034	−0.0056
	(0.0050)	(0.0060)	(0.0061)	(0.0061)	(0.0061)
m_TIER1_t	−0.0256***	−0.0076	−0.0049	0.0019	0.0006
	(0.0081)	(0.0091)	(0.0092)	(0.0095)	(0.0093)
m_TIER1_a:m_TIER1_t	0.0046	0.0027	0.0006	−0.0031	−0.0016
	(0.0102)	(0.0105)	(0.0106)	(0.0109)	(0.0107)
Observations	1,434	1,434	1,434	1,434	1,434
	CAR - Robustness - Relative size 20%				
	(1)	(2)	(3)	(4)	(5)
m_TIER1_a	−0.0272***	−0.0251**	−0.0252**	−0.0186*	−0.0195*
	(0.0090)	(0.0105)	(0.0107)	(0.0103)	(0.0106)
m_TIER1_t	−0.0437***	−0.0081	−0.0045	0.0107	0.0095
	(0.0115)	(0.0131)	(0.0134)	(0.0143)	(0.0140)
m_TIER1_a:m_TIER1_t	0.0274*	0.0241	0.0225	0.0111	0.0133
	(0.0146)	(0.0152)	(0.0154)	(0.0159)	(0.0157)
Observations	668	668	668	668	668

*p<0.1; **p<0.05; ***p<0.01

Table A.11: Robustness tests - Relative size cut-off - CWG / ASOCWG

This table shows the Tier1 coefficients of OLS regressions analyzing the relationship between adviser reputation and combined wealth gain (Regression (1) and (2)), and acquirer share of combined wealth gain (Regression (3) and (4)) respectively. For the purpose of robustness testing different realtive size thresholds are applied, resulting in different sample sizes. The regression set-ups correspond to those used in Table 11. In addition to the presented coefficients Regression (1) and (3) include deal specific characteristics and Regression (2) and (4) further include deal type dummies. Given the small sample size, no fixed effects are included in order to avoid overspecification issues. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	CWG & ASOCWG - Standard sample			
	(1)	(2)	(3)	(4)
m_TIER1	137.3906	82.9938		
	(277.3877)	(304.7645)		
m_TIER1_a			2.7399	2.8806
			(2.0046)	(1.9901)
m_TIER1_t			2.2114	2.6382
			(2.0577)	(2.0048)
m_TIER1_a:m_TIER1_t			−2.2569	−3.1948
			(2.5918)	(2.5581)
Observations	125	125	125	125
	CWG & ASOCWG - Robustness - Relative size 5%			
	(1)	(2)	(3)	(4)
m_TIER1	130.7289	82.6246		
	(257.6699)	(281.7256)		
m_TIER1_a			2.5341	2.6914
			(1.8042)	(1.7913)
m_TIER1_t			1.9640	2.7220
			(1.8522)	(1.8179)
m_TIER1_a:m_TIER1_t			−1.9348	−2.9691
			(2.3636)	(2.3177)
Observations	136	136	136	136
	CWG & ASOCWG - Robustness - Relative size 20%			
	(1)	(2)	(3)	(4)
m_TIER1	144.0200	96.7738		
	(326.9827)	(363.2157)		
m_TIER1_a			2.6114	2.3750
			(2.3068)	(2.3262)
m_TIER1_t			2.3730	2.5736
			(2.2903)	(2.2624)
m_TIER1_a:m_TIER1_t			−2.1351	−3.0953
			(2.8886)	(2.8774)
Observations	110	110	110	110

*p<0.1; **p<0.05; ***p<0.01

Table A.12: Robustness tests - Relative size cut-off - Deal completion

This table shows the Tier1 coefficients of probit regressions analyzing the relationship between adviser reputation and deal completion in the acquirer (Regression (1) and (2)) and target sample (Regression (3) and (4)). For the purpose of robustness testing varying relative size thresholds are employed. As those are only relevant for the acquirer sample, the target sample shows no changes. The regression set-ups correspond to those used in Table 13. In addition to the presented coefficients Regression (1) and (3) include deal specific characteristics as well as deal type dummies. Regression (2) and (4) further year and country fixed effects. The standard errors presented in brackets below the coefficients are corrected for heteroscedasticity.

	c_CLOSED - Standard sample			
	(1)	(2)	(3)	(4)
m_TIER1	−0.1106	0.0343	0.0771	0.1406
	(0.2052)	(0.2346)	(0.2223)	(0.2708)
Observations	1,021	1,021	400	400
	c_CLOSED - Robustness - Relative size 5%			
	(1)	(2)	(3)	(4)
m_TIER1	−0.1227	−0.0025	0.0771	0.1406
	(0.1958)	(0.2240)	(0.2223)	(0.2708)
Observations	1,413	1,413	400	400
	c_CLOSED - Robustness - Relative size 20%			
	(1)	(2)	(3)	(4)
m_TIER1	−0.0269	0.1811	0.0771	0.1406
	(0.2375)	(0.2746)	(0.2223)	(0.2708)
Observations	657	657	400	400

*p<0.1; **p<0.05; ***p<0.01