The Advising Investment Bank's Industry Expertise and Access to the Bidder's Private Information: Their Positive Influence on the Performance in Acquisition Sequences

by

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Abstract:

This study extents the literature of the advising bank's positive influence on the performance in mergers and acquisitions by modeling the expertise of banks on the industry level while considering two levels of endogeneity. The first level of endogeneity is caused by the most experienced banks being selected into the largest and most complex transactions with the lowest returns. The second level of endogeneity is caused by the observability of the influence of the bank's industry expertise on the performance only when the acquirer decided to employ a bank as advisor and to choose that bank in particular. Along the acquisition sequence the bank that is most familiar with the acquirer and that has the highest industry expertise in the acquirer's and target's industries is most likely to be chosen as advisor. The choice of the advising investment bank based on its industry expertise and its access to the acquirer's private information has a positive influence on the acquirer's returns. In the analysis of the alternative advisor choice by endogenous switching the employment of a more experienced bulge-bracket bank would have resulted in higher returns in transactions advised by non-bulge-bracket banks or that are unadvised. The analysis shows that the matching of the most experienced banks with the largest and most frequent serial acquirers in the most complex transactions is efficient in terms of higher returns and a higher completion probability.

Key Words:

Mergers & Acquisitions, Investment Banks, Acquisition Sequence, Industry Expertise, Advisory Relationship

JEL Classification Codes:

G34, G24

1. Introduction

This study sheds light on the positive influence that the acquirer's selection of the advising bank based on the performance in a previous acquisition of the acquirer it advised, its industry expertise in the target's industry and access to the acquirer's private information has on acquisition's performance. The positive influence the advising bank's industry expertise has on the returns, completion probability and resolution speed differs from the mixed and sometimes different observations previous studies made. Bao & Edmans (2011) for instance find an inverse relationship between the acquisition returns and the M&A league table ranking of the advising investment bank. Similarly earlier studies such as Rau (2000), Servaes & Zenner (1996), Ismail (2008), Hunter & Jagtiani (2003) and Ma (2006) find mixed results regarding the benefits that M&A advisors provide in terms of a better performance. The former studies however do not control for endogeneity of different types of banks advising different kinds of transactions and do not model the banks' expertise directly.

The first methodological innovation of this study is the direct measurement of banks' advisory expertise and access to information in each industry. The two studies that also observe a positive influence of advising investment banks on the acquirers' returns are Kale et al. (2003) and Golubov et al. (2010). In this study the advisory skills of investment banks are not assumed to be represented by a measure of reputation, the SDC Top-50 M&A League Table market share (Golubov et al. (2010), Kale et al. (2003), Rau (2000), Bao & Edmans (2011), Servaes & Zenner (1996), Ismail (2008), Hunter & Jagtiani (2003), Ma (2006)). The SDC M&A League Table market share is biased against smaller. The market share of bulge-bracket banks is ten times larger than the average market share of non-bulge-bracket banks. However, the average industry specific expertise of bulge-bracket banks is only three times larger than the industry expertise of non-bulge-bracket banks. Non-bulge-bracket banks are specialized in certain industries and thus advise fewer and smaller transactions than the bulge-bracket banks that operate in all industries (Song & Wei (2009). Modeling the expertise directly makes it possible to compare bulge-bracket banks, the top-10 banks in the SDC M&A League Tables, and non-bulge-bracket banks. The banks' industry expertise modeled as the fraction of M&As advised in the acquirer's and target's industries in the previous three years approximates their relative advisory experience compared to other banks and access to industry information. This direct measure of advisory skills is adapted and advanced from Chang et al (2008).

The second methodological innovation of this study is the controlling and modeling of two levels of endogeneity. First it is known that bulge-bracket banks self-select or are selected by larger companies into more complex and larger M&As that have lower returns than smaller and less complex deals advised by non-bulge-bracket banks (Chemmanur & Fulghieri (1994), Anand & Galetovic (2006), Moeller et al. (2004)). The lower returns of larger and more complex transactions are caused by higher transaction costs and not by the bulge-bracket banks themselves. Regressions without controlling for the endogeneity caused by the selection of the banks into different kinds of deals lead to the observation that a higher reputation measured by the SDC M&A League Table market share, as a proxy for advisory skills, is associated with lower returns. Controlling for endogeneity changes the observation of the employment of an advising bank with a higher reputation being associated with lower returns into the opposite result of the hired bank with its greater advisory-relationship strength and industry expertise being positively associated with the bidder returns.

The controlling of the second selection bias that the choice of the particular advising bank can be observed only for those deals in which the acquirer decided to employ a bank shows that the choice of the advisor based on his industry expertise and familiarity with the bidding company has a positive influence on the returns and completion probability. The modeling of the selection between non-bulge-bracket banks and bulge-bracket banks by Kale et al. (2003) and Golubov et al. (2010) is extended by controlling for the endogeneity caused by the decision whether to employ a bank as advisor at all and which individual bank in particular based on its industry expertise and advisory relationship strength with the bidder.

A further advancement is the answering of the question what the returns had been if the bidder had chosen another type of investment bank, for instance a bulge-bracket bank instead of a non-bulge bracket bank, or had not employed an advisor at all. The "what if" analysis of endogenous switching shows that better skilled banks provide higher returns for the acquirer than less skilled banks or the option not to employ a bank at all comparably to Golubov et al. (2010). The observations in previous papers of bulge-bracket banks being associated with on average negative bidder returns is misleading as the advice of the acquisition by less skilled banks or no advisor at all would have resulted in lower returns. The three-tier switching model extents the two-tier model of Golubov et al. (2010) by considering the alternative choice of not employing a bank to save advisory fees.

The final conceptual contribution of this study is the empirical analysis of the influence of investment banks as advisors on the acquirer's returns in acquisition sequences based on the neoclassical theory of mergers and acquisitions. The characteristics of the transactions and the acquisition experience of the bidding company change over the course of successive M&As and thus influence the need for the advisory skills of an investment bank as well as the returns and resolution speed (Fuller et al. (2002)). Investment banks have incentives to build advisory relationships over successive transactions with the most frequent acquirers to earn more fees from further advisory mandates (Anand & Galetovic (2006), Chemmanur & Fulghieri (1994), McLaughlin (1990, 1992)). This analysis shows that the building of advisory relationships and the matching of bulge-bracket banks with the largest and most frequent serial acquirers is efficient in terms of higher returns and completion probabilities due to bulge-bracket banks' on average high industry expertise. These empirical observations support the neoclassical theory of mergers and acquisitions (e.g. Maksimovic & Phillips (2001, 2002), Lang et al. (1989)). The companies with the largest investment opportunity sets, approximated by Tobin's Q, make more acquisitions with higher returns, supported by investment banks as financial intermediaries (Klasa & Stegemoller (2007), Hunter & Walker (1990), McLaughlin (1990, 1992)).

The empirical analysis is based on a sample of 40,961 mergers and acquisitions in the USA from 1979 until 2006 for all investment banks in the SDC M&A Universe. For each investment bank its industry expertise for the 49 Fama & French (1997) industries and relationship strength with the bidders is calculated in every year. The endogeneity is modeled with the two selection equations according to Poirier (1980).

A simplified analysis of the alternative advisor choice and its effect on the returns is based on an ordered-probit selection model of Heckman (1976, 1979). The ordered-probit selection regression models the discrete choice of no advisor, a non-bulge-bracket bank or a bulge-bracket bank as advisor. The structural regressions of the model are used to estimate the hypothetical returns if another type of advisor had been chosen in the "what if" analysis of endogenous switching.

In which way the results regarding the selection of investment banks and the selection's influence on the performance are obtained is subject of the next sections. Section 2 includes the development of the hypotheses. Section 3 describes the sample selection process and data preparation. Section 4 defines the variables used to model the decision whether to hire an investment bank at all, which bank to choose as advisor in particular, and the effect of the advisor choice on the performance. Section 5 includes the univariate analysis. Section 6 includes the multivariate analysis. Section 7 includes a simplified two stage ordered probit model comparable to previous studies. Section 8 describes the "what if" analysis of the realized and hypothetical returns. Section 9 concludes.

2. Literature review and hypotheses development

The basic assumption for the choice of an investment bank as advisor is that skilled investment banks provide a better matching between the acquirer and potential targets according to the arguments of Hunter & Walker (1990) and McLaughlin (1990, 1992). Investment banks as financial intermediaries reduce the informational asymmetry of acquisitions between the acquirer and the target (Servaes & Zenner (1996)). Investment banks facilitate the matching process by reducing the search costs of the acquirer by scanning the market for potentially profitable targets constantly. This scanning for potential targets reduces the informational asymmetry arising from the acquirer's incomplete information which companies might be fitting targets. To sum it up investment banks help their clients to find targets or acquirers with the highest expected synergies (Hunter & Walker (1990), McLaughlin (1990, 1992)). Servaes & Zenner (1996) argue that besides the informational asymmetry the higher the transaction costs, arising from the deal's complexity, and the contracting costs the more likely is the employment of a financial advisor in the M&A on the side of the acquirer. The job of the advising investment bank is to reduce these costs for the acquirer.

The contracting costs refer to potential agency problems such as managerial overconfidence, empire building or hubris in general (Roll (1986), Morck et al. (1990), Dong et al. (2006), Malmendier & Tate (2005a/b, 2008), Atkas et al. (2007, 2009)). The agency problems arise between the managers of the bidding company, its shareholders and possibly also the investment bank. According to Rau & Rodgers (2002) investment banks are hired to certify the value of the acquisition to shareholders that the management is not empire building and that the M&A adds value. The bank itself has no interest to get involved in any agency conflict with the management and the shareholders. Such a conflict might hurt the bank's reputation (McLaughlin (1990, 1992)).

Given the transaction costs Atkas et al. (2007, 2009) and Servaes & Zenner (1996) argue that experienced acquirers are less likely to need the advice of a bank because of their learned ability to reduce these costs themselves. This assumes that the CEO or the CFO are not suffering from hubris or engage in empire building but are rationally acting in the interests of the shareholders. This leads to the first hypothesis.

Hypothesis 1 (Decision to employ a bank)**:** *The probability to employ a bank as advisor is increasing in the transaction costs, the contracting costs and the informational asymmetry and decreasing in the acquirer's acquisition experience. The acquirer's acquisition experience is increasing in the acquisition skills learned in previous transactions.*

Besides the decision to employ a bank as advisor the particular investment bank i as advisor is chosen based on its ability to reduce the transaction cost, to mitigate the contracting costs and to reduce the informational asymmetry. According to the neoclassical theory of mergers and acquisitions the bank's ability to reduce the informational asymmetry depends on its access to information about the acquirer, the target or potential targets and the competitive environment of the acquirer's and target's industries. The investment bank's skills are needed to reduce the transaction costs by executing the M&A more efficiently and to reduce the contracting costs by certifying the value of the M&A to the shareholders. The investment bank's skill and access to information are expected to increase in the number of M&As advised. The bank has learned how to generate value for its clients in the M&As (Chemmanur & Fulghieri (1994), Kale et al. (2003), Chang et al. (2008)). A further assumption is that the information is specific to each industry. The same industry specificity is to a smaller degree likely to hold for the investment bank's skills. Advising M&As between financial institutions in the banking sector has different challenges, for instance regulatory requirements, than advising M&As in the airline or automobile industries. In these regards the industry expertise is the combination of the learned investment bank's skills and information gathered from advising previous transactions in the particular industry (Chemannur & Fulghieri (1994), Kale et al. (2003), Chang et al. (2008)).

The same holds for the bank's access to private information of the acquirer. The bank can advise more deals to gather more private information in an ongoing relationship. The private information of the acquirer helps the bank to identify the acquirer's strengths and weaknesses. The bank can assess the either rational managerial motives, such as the exploitation of investment opportunities caused for instance by industry shocks, or the hubris driven motives behind the M&A (Roll (1986), Malmendier & Tate (2005a/b, 2008), Andrade & Stafford (2004), Andrade et al. (2001), Harford (2005), Maksimovic & Phillips (2001, 2002)).

The relationship with the acquirer enables the investment bank to obtain private information about the acquirer that is not available to external investment banks. In the relationship the bank and the acquirer engage in a win-win situation. For the relationship bank it is easier to get the advisory mandate compared to external banks as it is more familiar with the acquirer and knows more about him. The acquirer gets better informed advisory services at lower transaction costs (Anand & Galetovic (2006), Chammanur & Fulghieri (1994), Kale et al. (2003)). The bank's access to information is increasing the more intensive the relationship with the acquirer is. Acquirers are expected to be more likely to hire banks with which they have a strong advisory relationship (Forte et al. (2007), Chang et al. (2008)). The two characteristics of the access to private acquirer information and the industry expertise are expected to be important determinants of the advisor choice in any stage of the acquisition sequence. The second hypothesis captures these arguments.

Hypothesis 2 (Particular advisor choice)**:** *The probability of the bank to be chosen as advisor is increasing in its past advisory performance, its access to information in the industries of the acquirer and the target and its access to the private information of the acquirer.*

The expertise of the advisor is expected to complement the acquisition experience of the acquirer to make shareholder value increasing acquisitions even when the investment opportunity set is diminishing (Klasa & Stegemoller (2007)). According to Klasa & Stegemoller (2007) serial acquirers make several acquisitions to exploit growth opportunities according to the neoclassical theory of mergers and acquisitions (Gort (1969), Mitchell & Mulherin (1996), Maksimovic & Phillips (2001, 2002), Harford (2005)). The targets with the largest synergies are acquired first. Therefore the announcement returns are expected to be higher in the beginning of the sequence than at the end (Atkas et al. (2007, 2009), Ahern (2008), Fueller et al. (2002)).

If the benefits of an acquirer-advisor relationship with an advisor who has industry expertise exceed the costs of the advisory service in comparison of doing the acquisitions without advice the advisor choice and maintenance of the relationship would be beneficial for the acquirer. The observation of ongoing relationships between serial acquirers and advisors would explain the pyramidal structure of the investment banking industries modeled theoretically by Anand & Galetovic (2006) and Chemmanur & Fulghieri (1994). This assumes that the bulge-bracket banks have a greater industry expertise and build stronger acquirer-advisor relationships than smaller banks due to the large number of transactions they advise. It follows that a greater industry expertise of the financial advisor in the acquirer's and target's industries ought to result in higher

M&A performance by finding targets that match the acquirer and by supporting the acquirer in the bidding and structuring of the transaction. These arguments lead to the third hypothesis:

Hypothesis 3 (Higher performance): *The choice of the advising investment bank based on its industry expertise and familiarity with the acquirer results in a higher M&A performance due to the advisor's greater advisory skills and access to information in the acquirer's and target's industries.*

Nevertheless, the mixed evidence on the performance of M&A advisors, and bulge-bracket banks in particular, is puzzling given their task to reduce the transaction costs, contracting costs and the informational asymmetry between the acquirer and the target about the unknown present value of the target. Rau (2000) found out that the market share of an investment bank does not depend on the past returns of advised deals, but the number of completed deals. Moreover, Rau (2000) discovered that acquirers advised by bulge-bracket banks earn lower announcement returns and pay higher acquisition premia. Ismail's (2008) results are similar for reputable investment banks. In a comparable vain Hunter & Jagtiani (2003) show that the returns are lower and the speed of completion is slower, while the probability of completion similarly to Rau (2000) is higher when employing a bulge-bracket bank. On the target's side Ma (2006) shows that the employment of a reputable financial advisor does not hurt the acquirer. Servaes & Zenner (1996) do not find that the employment of a bank as advisor has an advantage compared to seeking advice in-house. Bao & Edmans (2011) discovered that the performance of M&A advisors with respect to the announcement returns is persistent as acquirers do not chase performance. The smaller investment banks have significantly higher persistent returns than the bulge-bracket banks. So far Kale et al. (2003) and Golubov et al. (2010) are the only ones that show a positive effect of using a financial advisor with a relatively greater reputation than that of the target advisor. To solve the puzzle of often opposing empirical results a dataset of mergers and acquisitions of all kinds and sizes from 1979 to 2006 is used.

3. Construction of the data set

To examine the hypotheses the analysis focuses on acquirers that make at least one acquisition or more, because repeat acquirers make approximately 67.3% of all acquisitions and are among the largest companies. The use of a sample of one-time and multiple acquisitions is necessary to analyze empirically the effect of the advisor choice on the returns of acquisition sequences. The sample of mergers and acquisitions is taken from the SDC Mergers & Acquisitions database. It includes mergers and acquisitions with a disclosed transaction value. All targets are located in the USA to avoid the problems caused by different currencies and jurisdictions arising in cross-border M&As with targets outside the USA.

The initial sample includes 208,654 acquisition or bids from 01/01/1979 to 12/31/2008. The acquisition or bids are mergers and acquisitions of all kinds. The sample includes transactions in which the acquirer intents to acquire all or a part of the assets of another company. This sample is cleaned from incomplete records and finally includes bids or acquisitions with reported transaction values, where the acquirer and target are different and identifiable companies, and the status indicates that a bid or acquisition has actually taken place. These bids and acquisitions are chosen because they represent the attempted or completed M&As of companies that want to acquire the assets of another company for strategic reasons. Acquisition sequences are a strategic option of external growth for the bidding companies to exploit their investment opportunities (Klasa & Stegemoller (2007)). The sample selection and data preparation process is summarized in Table 1A.

Insert Table 1 here

Sample A includes 65,661 acquisitions or bids before the merging with Compustat. It is used to calculate the industry expertise of the banks in the target's and acquirer's industry, the acquirer-advisor relationship strength for each bank and each acquirer and the annual number of investment banks available as potential advisors. The sample of 65,661 acquisitions or bids shrinks further, because not for all bidding companies are the Compustat data available. The merging with Compustat causes a bias towards large companies whose financial information is collected in Compustat. After merging with Compustat 40,961 acquisitions or bids are left from 01/01/1979 to 12/31/2006.

As sample B and C used to test hypothesis 1 and 3 includes single bids as well as very long acquisition sequences its size of 40,961 observations is larger than the samples of sequences of up to five bids used in previous research (Fuller et al. (2002)). Particularly the effects at the sixth and later acquisition or bid are investigated as previous studies have mostly focused on sequences with one to five acquisitions due to an implicit convention in the literature (e.g. Ahern (2008), Fuller et al. (2002), Atkas et al. (2007, 2009)).

It follows that the definition of an acquisition sequence is everything in excess of one acquisition without any limitation or minimum requirement of the length of the acquisition sequence. Also no minimum number of bids in a specified time period such as five bids in three years (e.g. Fuller et al. (2002)) is stipulated to avoid a bias towards serial acquirers that make many smaller acquisitions in short succession. The bias is avoided also as it is unknown whether the post-merger integration is completed after four weeks or four years with the next M&A following directly afterwards. The avoidance of any restriction on the time between successive transactions results in an average time gap of 521 days that is longer than in other studies (e.g. Ahern (2008), Croci & Petmezas (2009)). Nevertheless the pattern of decreasing gaps between the successive bids within the acquisition sequence is similar to the pattern observed by Atkas et al. (2009) and predicted by their theory that with acquisition experience the acquisitions are made in shorter succession. The average time gap of 796 days between the first and second bid decreases to 300 days between the sixth or later bid (See Table 1B).

The final sample of 40,961 acquisitions or bids includes 13,683 different acquirers. M&A announcements occurring on the same day are considered as one announcement. 47.42% of the 13,683 acquirers make a single one-time bid or acquisition, 39.19% of all acquirers have two to five bids in their acquisition sequences, while 13.39% of all acquirers have acquisition sequences with six or more bids. It follows that 13,409, or 32.7%, are first time or single acquisitions, 17,077 or 41.2% are the second to fifth acquisition or bid and the remaining 10,475, or 26.1%, acquisition are the sixth or later ones. Therefore the restriction to five bids had resulted in the same fraction of approximately 38% of two to five bids or acquisitions as for instance Ahern (2008) has found in his sample. It follows that the 1,832 or 13.39% of all acquirers make six or more acquisitions or bids and account for one quarter of all transactions. The bottom line of these descriptive statistics is that acquisition sequences are important as more than 50% of all acquirers make several acquisitions. The restriction to sequences with one to five transactions had left out more than one quarter of all M&As occurring in acquisition sequences. However, the 13,683 acquirers make on average 3 acquisitions. The distribution of transactions in each year, the number of banks in the SDC M&A universe and the League Tables and the actual and possible acquisition-bank matches are shown in Table 1C. The variables used to analyze the advisor choice of the serial acquirers and the influence of this choice on the performace in the acquisition sequences is subject of the next section.

4. The construction and description of the variable to test the hypotheses

4.1 The dependent variables

To test hypothesis 1 that the probability of the M&A being advised depends on the transaction's complexity has to be estimated by a probit regression. The dependent variable ADVISED is a dummy variable that is 1 when the bid or acquisition j is advised by at least one investment bank and 0 otherwise (See Tables 2A & 3A). To test hypothesis 2 the dependent variable is the dummy $\text{AADVISOR}_{i,j,t}$, which is 1 if investment bank i has been chosen in the acquisition or bid j at time t as advisor (See Tables 2A & 3A). In the tests of hypothesis 3 the dependent variable CAR (-1, 1) value weighted are the cumulative abnormal returns from 1 day before to 1 day after the announcement of the M&A (See Tables 2A & 3A). The returns are calculated with the market model CAPM calibrated from -270 to -20 days before the announcement using the CRSP value weighted index. The dummy COMPLETED is 1 if the transaction has been completed (See Tables 2A & 3A). The variable RESOLSPEED is the time in days from the announcement until the completion or withdrawal of the M&A (See Tables 2A & 3A). The variable ADVISORFEE are the advisor fees of the acquirer's advisor reported by SDC (See Tables 2A & 3A). Finally in the sensitivity analysis using the two-stage ordered probit analysis of Heckman (1976, 1979) and Vella (1992, 1993, 1998) that simplifies the empirical testing of hypotheses 1 and 2 into one regression equation the dependent variable ADVISORCHOICE is 1 if no advisor is chosen, 2 if the chosen bank is a non-bulge-bracket bank and 3 if the chosen bank is a bulge-bracket bank (See Tables 2A & 3A).

Insert Tables 2 and 3 here

4.2 The independent variables to model the banks' characteristics and their expertise

The independent variables used to approximate the access of the investment banks to information in the acquirer's and target's industries and to the acquirer's private information are adapted and modified from previous research (Chang et al. (2008), Forte et al. (2007), Saunders & Srinivasan (2001)). The industry expertise $\text{IE}_{i,k,t}$ is the sum of the investment bank's i investment banking skills and its access to information in industry k at time t. The approximation of the industry expertise is based on the M&As advised in the past three years. A larger number of advised M&As is associated with more information being available about the advised companies and their competitive environment. With more transactions advised the bank learns how to advise M&As better by accumulating advisory skills (Chemmanur & Fulghieri (1994), Chang et al. (2008)) (See Tables 2B & 3B).

The industry expertise is measured either by the number of acquisitions advised with respect to the total number of advised acquisitions j=1,…,N in each of the k=1,..,49 Fama & French (1997) industries in the three years t-1, t-2, t-3 preceding the year t of the acquisition or bid. The industry expertise is a relative measure that compares the bank's industry expertise relative to the expertise of other banks who advised acquisitions or bids in the industry k. The measure of the industry expertise of bank i in industry k with k=1,…, 49 in year t measured by the relative number of deals advised is defined as

$$IED_{i,k,t}=\frac{\left(\frac{advised\_deals_{i,k,t-1}}{advised\_industry\_deals_{k,t-1}}+\frac{advised\_deals_{i,k,t-2}}{advised\_industry\_deals_{k,t-2}}+\frac{advised\_deals_{i,k,t-3}}{advised\_industry\_deals_{k,t-3}}\right)}{3}$$

When for instance the advised acquirer is from the ship building industry, while the advised target is from the transportation industry, the acquisition or bid is counted in the year of the announcement once for the ship building industry and once for the transportation industry. If the target and the acquirer both are advised and are from the same industry the acquisition or bid is counted only once for the industry to avoid double counting. The double counting is avoided, because an investment bank can advise either the target or the acquirer, but not both parties at the same time. The avoidance of double counting ensures that an investment bank which participated in an industry in every transaction as advisor on either the target's or the acquirer's side has the maximum industry expertise of 1. Only acquisitions or bids that are advised on the acquirer side, the target side, or on both sides are counted for the number of advised deals.

For instance in the year 1998 Goldman Sachs had an industry expertise by acquisitions or bids advised in the ship building industry of 0.1111. This is computed by the number of M&As Goldman Sachs advised in the preceding year 1997 divided by the number of all advised M&As in the ship building industry in 1997, which is 1/3. Goldman Sachs did not advice any acquisition or bid in the ship building industry in the years 1996 and 1995. The industry expertise of Goldman Sachs in 1998 is

$$IEDA_{1998}=\left(0.\overline{3}+0+0\right)/3=0.\overline{1}$$

The normalization with 3 ensures that the industry expertise by advised acquisitions or bids is a ratio between 0 and 1. The maximum industry expertise of 1 corresponds to 100% when Goldman Sachs had participated as advisor on the acquirers' or targets' sides in all advised acquisitions or bids in the ship building industry within the preceding three years. The variable for the industry expertise based on the number of deals in the acquirer's and the target's industries are IEDA and IEDT (See Tables 2B & 3B).

The calculation of the proxy for the access to the information $I_{i,B,t}$ of acquirer B of bank i at time t is similar to the calculation of the proxy for the industry expertise. The proxy for the access to the acquirer information is the advisory relationship strength ARS based on the arguments of Anand & Galetovic (2006) that the building of relationships by investment banks with the bidding companies enables the banks to get access to the private information of the acquirers. The advisory relationship strength is based on the number of M&As bank i advised with respect to the number of all advised M&As the acquirer conducted in the three years preceding the acquisition or bid considered. In this case the strength of the advisory relationship is a relative measure compared to the strength of the advisory relationships the acquirer has with other banks. The variable for the advisory relationship strength is ARSD (See Tables 2B & 3B).

Additionally the advisor's market share MS as reputation proxy is used. A higher reputation is associated with better investment banking skills in previous studies (Kale et al. (2003), Rau (2000), Carter & McManaster (1990)). The market share of the investment bank is taken from the SDC Top-50 M&A League Tables according to Rau (2000), Servaes & Zenner (1996), Sun et al. (2005) and Kale et al. (2003) (See Tables 2B & 3B). The market share MS of investment banks not included in the SDC Top-50 M&A League Tables is set to the minimum of 0.1. Related to the market share MS is the relative reputation RELREP, which is the acquirer's advisor's market share MS divided by the target's advisor's market share (Kale et al. (2003)). If the target does not employ an advisor the variable RELREP is not available as division by 0 is not possible (See Tables 2B & 3B).

Finally the past performance of the M&As advised by banks is modeled comparably to Rau (2000) and Hunter & Jagtiani (2003). PASTACAR is the value weighted CAR (-1, 1) of the acquirer's previous M&A if it was advised by the bank. It is the past CAR $(-1, 1)_{i-1}$ multiplied with the dummy (0/1) if the CAR $(-1, 1)_{i-1}$ is available (See Tables 2B & 3B). PASTCOMPLETED is a dummy (0/1) whether the bank completed the M&A if it advised the acquirer in a previous deal (See Tables 2B & 3B). PASTRESOLSPEED is the time in days from 0 to 730 from the announcement to the completion or withdrawal date to resolve the M&A if the bank advised the acquirer in a previous deal (See Tables 2B & 3B).

The calculation of the industry expertise, the advisory relationship strength, the market share and the past performance variables requires the tracking and controlling of bank mergers and banks' name changes. The assumption is that the merging banks inherit the expertise and advisory relationships of their predecessors. The ultimate parent of the banks has inherited all relationships and industry expertise of the former banks. Table B in the online appendix includes the bank mergers and name changes of all 201 banks in the SDC Top-50 M&A League Tables from 1979 to 2006 together with their ultimate parents as of 12/31/2006[2]. The methodology to track the name changes and bank mergers is adapted from Ljungqvist et al. (2006) and Carter & Manaster (1990) using a research in den LexisNexis press database and the banks' websites and annual reports. The implicit assumption is that key bankers who embody the experience and relationships with clients stay with the bank after mergers, acquisitions or name changes (Ertugrul & Krishnan (2009)). The name changes and mergers of banks not in the SDC Top-50 M&A League Tables are not tracked, because sample B includes 1,867 different banks from 1979 to 2006. The 201 banks in the League Tables advise approximately 75% of all M&As.

4.3 The independent variables to model the acquirers' characteristics

The acquisition experience of the acquirer is approximated by the number of bids or acquisitions he conducted in the previous three years, measured by the variable DEALS3YEARS (Servaes & Zenner (1996)) (See Tables 2C & 3C).

To be able to conduct M&As the bidding company needs the appropriate resources. The ability to bid for target companies increase in the free cash-flow available to finance the acquisition. The free cash flow is measured with the variable FCF calculated according to Lang et al. (1991). Opposing the effect of a high free cash flow is a high leverage that constraints the management in its debt financing to acquire other companies. The leverage is controlled using the variable LEVERAGE according to Masulis et al. (2007) and Moeller et al. (2004) (See Tables 2C & 3C).

Besides a larger amount of resources being available to spend on acquisitions a larger investment opportunity set is expected to provide more profitable acquisition opportunities. The assessment of the investment opportunities by the market is modeled with Tobin's Q adapted from Andrade & Stafford (2004) (See Table 2C). Similarly to all other continuous variables TobinsQ is winsorized at the upper and lower 1% percentile as well as FCF and ROA, which are calculated according to Lang et al. (1991), Bao & Edmans (2011) and Moeller et al. (2004, 2005) (See

[2] Table B is available in the appendix online at http://voget.bwl.uni-mannheim.de/index.php?id=45 .

Table 2C). The return on assets ROA is used an approximation of the acquirer's profitability (See Tables 2C & 3C).

All mentioned variables measure the individual acquirer's characteristics. According to the neoclassical theory of mergers and acquisitions those companies with the highest profitability and largest set of investment opportunities compared to the other companies in the industry are going to acquire other companies (Andrade & Stafford (2004), Mitchell & Mulherin (1996), Maksimovic & Phillips (2001, 2001), Harford (2005), Klasa & Stegemoller (2007)). The size of the set of investment opportunities and the profitability are also measured relative to the industry average. The average industry leverage is controlled with the variable ILEVERAGE, which is the mean leverage of the Fama & French (1997) industry computed to the acquirer's leverage (See Table 2C & 3C). The average industry Tobin's Q as ITobinsQ and average industry ROA as IROA are similarly defined as ILEVERGE (See Tables 2C and 3C). The size of the industry is measured with the discrete variable IS as the number of companies in the industry in the year before the bid or acquisition (See Tables 2C & 3C).

4.4 The independent variables to model the transaction characteristics

The transaction variables must approximate the transaction's contracting costs and the informational asymmetry. The informational asymmetry is approximated by several variables. M&As across industries increase the informational asymmetry. The first one is the dummy DIVERS for a diversifying acquisition (Servaes & Zenner (1996), Chang et al. (2008)) (See Tables 2D & 3D). The target's industry diversification is measured by the continuous variable DIVERSIFICATION (Servaes & Zenner (1996)) (See Tables 2D & 3D). For a controlling acquisition more information are needed. The purchase of a company is modeled with the variable MAJORITY that is 1 when the acquirer intends to obtain a controlling majority of the target company (Servaes & Zenner (1996)) (See Tables 2D & 3D). When the target or the acquirer or both are operating in high-tech industries and have a large share of assets in immaterial intangibles the informational asymmetry is high. Whether the M&A is one in high-tech industries is measured by the dummy HIGHTECH (Loughran & Ritter (2004)) (See Tables 2D & 3D). The acquirer's insider information about the target is assumed to decrease the informational asymmetry. This access to insider target information is measured by the continuous variable TOEHOLD (Song & Wei (2009), Kale et al. (2003), Servaes & Zenner (1996)) (See Tables 2D & 3D).

The relatively larger targets have a relatively better bargaining power which increases the transaction costs (Servaes & Zenner (1996), Ahern (2008), Fueller et al. (2002), Moeller et al. (2004, 2005)). The relative deal size is measured with the continuous variable RDS (See Tables 2D & 3D). The existence and consideration of competition from multiple acquirers makes the acquirer's bidding strategy more complex, modeled by the variable MULTIPLE (Servaes & Zenner (1996), Boone & Mulherin (2008)) (See Tables 2D & 3D).

The last variables modelling the complexity of the transaction are dummy variables adapted and extended from Kale et al. (2003). The first dummy ANTITAKEOVER controls for anti-takeover measures (Comment & Schwert (1995)). The second dummy CROSSBORDER controls for cross-border deals (Jong et al. (2008)). The third dummy REGULATORY models the need of regulatory approval, the fourth one FAMILY family ownership, and the fifth one LITIGATION a pending litigation against the target. Kale et al. (2003) show that the acquirer advisor choice depends on the target's advisor's tier, which is modelled with the discrete variable TADVISORTIER (See Tables 2D & 3D). A hostile acquisition is more complex and increases the costs to remove the resistance of the target's management (Servaes & Zenner (1996), Schwert (2000)). The dummy HOSTILE is set to 1 when SDC labels the transaction as hostile.

A merger and a tender offer are also more complex than the acquisition of a company or its assets. The higher complexity of mergers and tender offers that increase the transaction costs are modeled with the dummies MERGER and TENDER (Atkas et al. (2007, 2009), Boone & Mulherin (2008)). In a merger of equals the two merging companies' shares in the new company and the financing and share of stockholders' equity tailored towards the new ownership structure have to be negotiated (Servaes & Zenner (1996), Jaffe et al. (2008), Atkas et al. (2007, 2009)). The dummy MERGEREQUAL is set to one when SDC labels the transaction as a merger of equals.

The payment by stock increases the complexity and thus the transaction costs as well as the shares of the acquirer have to be valued to determine how many shares the acquirer has to bid for one share of the target company (Servaes & Zenner (1996), Chang (1998), Fuller et al. (2002), Chang et al. (2008), Song & Wei (2009)). The dummy SOMESTOCK is set to 1 when at least some stock is used for payment.

Dummies for the stages of the acquisition sequences are also used. A dummy FIRST is one when the acquisition or bid is the first one of the bidding company in the data set. The dummy SIXTH is set to one when the transaction is the sixth and later one of the bidding company. The controlling of the stages of the acquisition sequence is necessary as the characteristics of the transactions, the bidding companies and the chosen advising investment banks change over the course of the acquisition sequence (Fuller et al. (2002), Ahern (2008), Atkas et al. (2007, 2009)). The change in the characteristics of the banks as advisors, the acquirers and the transactions is subject of the univariate analyses.

5. The univariate analysis to examine the advising banks, acquirer and transaction characteristics along the acquisition sequences and by the type of advisor

The univariate analysis examines the differences in the advisor, acquirer, and transaction characteristics over the acquisition sequence as well as between the advisor types. The distribution of the variables is of interest before the probit regressions to check whether the advisory relationships and the transaction characteristics change over the acquisition sequence and differ between the M&As that are unadvised or advised by non-bulge-bracket banks and by bulge-bracket banks.

Insert Tables 4 and 5 here

The definition of a non-bulge-bracket bank and a bulge-bracket bank is adapted from Hunter & Jagtiani (2003) and Rau (2000). A bank is defined as a bulge-bracket bank if it has an annual rank of 10 or higher based on its weighted ranks of the last three years in the SDC Top-50 M&A League Tables. A non-bulge-bracket bank is defined to have a weighted rank of 11 or less. To avoid a look-ahead bias and to adjust for the perceived ranking of investment bank i over the years t the rank in each year t is the sum of the equally weighted ranks of the current year t=0 and the preceding two years t-1 and t-2. The formula is

$$\mathrm{NewRank}_{t,\,i} = \left(\mathrm{rank}_{t,\,i} + \mathrm{rank}_{t-1,\,i} + \mathrm{rank}_{t-2,\,i}\right)/3$$

The distribution of the advisor characteristics over the acquisition sequence shows that the industry expertise in the acquirers' and targets' industries of the bank chosen as advisor increases significantly over the acquisition sequence. Hence more experienced advisors are chosen in later acquisitions (See Table 4B). The bulge-bracket banks have a significantly higher industry expertise and advisory relationship strength than the non-bulge-bracket banks and are chosen more often as advisors in advised bids or acquisition in later stages of the acquisition sequence (See Table 5A).

It follows that the expected repeat interaction of the advising banks with the acquirers results in a greater familiarity after several acquisitions. This supports the theoretical model of Anand & Galetovic (2006) that the largest and most frequent acquirers have stronger advisory relationships with the larger investment banks that have incentives to propose deals to receive the advisory mandates (See Tables 4B and 5A). The likelihood to choose a known advisor hints at the positive effect the increasing advisory relationship strength has on the choice of the particular bank as advisor (See Tables 4B and 5A).

The acquirer increases his acquisition experience along the acquisition sequence (See Table 4C)[3]. The bidder's B growth in acquisition experience ought to come along with the exploitation of the investment opportunities in the investment opportunity set $\Omega_{B,t}$. Tobin's Q as a measure of the size of $\Omega_{B,k,t}$ is not diminishing along the acquisition sequence (See Table 4C). The higher average industry ITobinsQ hints at the results of Klasa & Stegemoeller (2007) that serial acquirers in industries with the largest investment opportunities make more acquisitions to exploit these opportunities. In line with the exploitation of investment opportunities in the industry are the diminishing returns that fall from 0.0114 in the first bid or acquisition to 0.0015 in the sixths and later one (See Table 4A). This phenomenon of falling announcement returns has been observed as well in previous studies looking at acquisition sequences, because the most profitable targets are acquired first (Ahern (2008), Fuller et al. (2002), Atkas et al. (2007, 2009). Together with larger industry investment opportunities those companies with higher returns on assets ROA as well as a higher free cash-flow FCF make more acquisitions (See Table 4C). The acquirers' industries are larger as well in later bids or acquisitions, because the average industry size increases from 1,010 companies in the first bid to 1,251 in the sixth and later transaction (See Table 4C). This hints as well to the neoclassical argument that more profitable companies with more investment opportunities make more acquisitions (Klasa & Stegemoller (2007)).

Regarding the deal characteristics the later acquisitions or bids are more complex as more often targets with a higher industry diversification are acquired or bid for, involving more often regulatory issues and anti-takeover defenses (See Table 4D). It follows that the increasing acquirer-advisor matching with familiar advisors with a higher industry expertise in later acquisitions or bids coincides with the increasing transaction costs and information asymmetries of the transactions (Servaes & Zenner (1996)). However, the fraction of cross-border

[3] The full Table 4, including panels C and D, is available online in the appendix at http://voget.bwl.uni-mannheim.de/index.php?id=45 .

transactions is diminishing and the acquirer has a toehold in the companies he bids for in later stages of the acquisition sequence, which reduces the information asymmetry (See Table 4D).

Bulge-bracket banks are more often the advisors of choice in later transactions that are also follow-on transactions (See Table 5A & 5C)[4]. The bulge-bracket banks more often advise the larger acquisitions of targets operating in many industries involving regulatory issues and cross-border transactions as well as anti-takeover defenses, more reputable advisors on the target's side and more competing acquirers compared to unadvised M&As or deals advised by non-bulge-bracket banks (See Table 5C). Furthermore the bulge-bracket banks more often advise larger acquirers with a larger return on assets and free cash-flow compared to non-bulge bracket banks and unadvised M&As (See Table 5B). These observations are comparable to Fang (2005) who found out that investment banks with a higher reputation issue higher quality debt. To reduce the informational asymmetry arising from the targets' operations in several industries the higher industry expertise in those industries compared to non-bulge-bracket banks is an advantage (See Table 5A). The increasing complexity and size of later acquisitions results in higher advisor fees (See Table 4A). Bulge-bracket banks advise larger and more complex transactions than non-bulge-bracket bank, which results in higher advisor fees and a higher resolution speed in bulge-bracket bank advised transactions (See Table 5A).

Finally the univariate analysis provides the first empirical support for hypotheses 1 and 2 that investment banks with a higher industry expertise and familiarity with the acquirer are more often chosen as advisors in complex transactions. Similarly to Fuller et al. (2002) the transaction characteristics as well as the acquirer and advisor characteristics change in follow-on transactions along the acquisition sequence. Whether these preliminary results for hypotheses 1 and 2 are supported by the probit regression analysis and whether the choice of the investment bank as advisor affects the performance is the subject of the multivariate analyses.

6. The multivariate analysis to test hypotheses 1 to 3 and while controlling for potential endogeneity

6.1 The probit regression to test hypothesis 1 whether the M&A is advised

To test hypothesis 1 that the likelihood of the M&A being advised increases with the transaction and contracting costs as well as the informational asymmetry and is decreasing the more

[4] The full Table 5, including panels C and D, is available online in the appendix at http://voget.bwl.uni-mannheim.de/index.php?id=45

experienced the acquirer is a probit regression comparable to Servaes & Zenner (1996) is estimated and shown in table 6. As mentioned before the dependent variable is the dummy ADVISED (See Tables 2A & 3A).

Insert Table 6 here

The informational asymmetry is approximated by several variables. The variables approximating the informational asymmetry between the acquirer and the target are DIVERS, DIVERSIFICATION*,* MAJORITY, HIGHTECH, and TOEHOLD (See Tables 2D & 3D). For the informational asymmetry $\Delta I_{j,t}$ it follows that it is a function of these variable.

$$\Delta I_{j,t} = \beta_0 + \beta_1 \times DIVERS_{j,t} + \beta_2 \times DIVERSIFICATION_{j,t} + \beta_3 \times MAJORITY_{j,t} + \beta_4 \times HIGHTECH_{j,t} \\ + \beta_5 \times TOEHOLD_{j,t} + \varepsilon_{j,t}$$

The transaction costs increase with the size and complexity of the M&A. The transaction costs are approximated by the variables RDS, MULTIPLE, ANTITAKEOVER, CROSSBORDER, REGULATORY, FAMILY, LITIGATION, HOSTILE and TADVISORTIER (See Tables 2D & 3D). On the other hand a more experienced acquirer is expected to be able to handle the complexity of an M&A and thus less likely to need an advising bank, which is approximated with the variable DEALS3YEARS (See Tables 2C & 3C).

The acquisition technique, the description of the mood of the M&A and the means of payment are usually determined by the advising investment bank if it pitches a deal to the CEO and CFO or is hired by them (Golubov et al. (2010), Bao & Edmans (2011)). However, the direction or causality of the decision whether to employ an investment bank is not observable. Particularly the labeling of the M&A being hostile is often subject to the target's bidding strategy and determined in consultation with its M&A advisor (Schwert (2000)).

One can conclude that the coefficients of the variables modeling the transaction costs are expected to be positively associated with an increasing probability to employ an investment bank. The transaction costs $TC_{j,t}$ are finally a function of the form of

$$TC_{j,t} = \beta_0 + \beta_1 \times RDS_{j,t} + \beta_2 \times MULTIPLE_{j,t} + \beta_3 \times ANTITAKEOVER_{j,t} + \beta_4 \times FAMILY_{j,t} \\ + \beta_5 \times LITIGATION_{j,t} + \beta_6 \times REGULATORY_{j,t} + \beta_7 \times CROSSBORDER_{j,t} \\ + \beta_8 \times TADVISORTIER_{j,t} + \beta_9 \times DEALS3YEARS_{B,t} + \beta_{10} \times HOSTILE_{j,t} + \varepsilon_{j,t}$$

The contracting costs are the costs of agency problems between the management of the bidding company and the shareholders. Larger acquirers are expected to have more resources available such that the management can engage in empire building (Roll (1986), Jensen (1986), Lang et al. (1991)). In acquisitions by large companies the board might insist on the opinion of an investment bank whether the acquisition is valuable to certify the transaction's value (Rau & Rodgers (2002)). The contracting costs are expected to increase in the cash available as a high free cash flow FCF can induce empire building (Jensen (1986), Lang et al. (1991)). Opposing the effect of a high free cash flow is a high leverage LEVERAGE that constraints the management in its attempts of empire building by limiting the ability to spend the cash freely (Dong et al. (2006), Masulis et al (2007), Moeller et al. (2004)). However, a high free cash-flow FCF and a high return on assets ROA that accompany a large set of investment opportunities approximated by TobinsQ and ITobinsQ and a large industry IS are expected to be positively associated with profitable and advised acquisitions (Andraide & Stafford (2004)). Finally the contracting costs $CC_{j,t}$ are a function of the form of

$$CC_{j,t}=\beta_0+\beta_1\times ROA_{B,t}+\beta_2\times LEVERAGE_{B,t}+\beta_3\times FCF_{B,t}+\beta_4\times IS_{B,k,t}+\beta_5\times ITobinsQ_{B,k,t}+\beta_6\times TobinsQ_{B,t}+\varepsilon_{j,t}$$

Dummies for the stages of the acquisition sequences are also used. A dummy FIRST is one when the acquisition or bid is the first one of the bidding company in the data set. The dummy SIXTH is set to one when the transaction is the sixth and later one of the bidding company. The controlling of the stages of the acquisition sequence is necessary as the characteristics of the transactions, the bidding companies and the chosen advising investment banks change over the course of the acquisition sequence as shown in Tables 4 and 5 (Fuller et al. (2002), Atkas et al. (2007, 2009), Ahern (2008)). The final regression equation [1] to estimate the probability that the M&A is advised is

$$P(ADVISED_{j,t}=1)=f(\Delta I_{j,t}, TC_{j,t}, CC_{j,t}) \quad [1]$$

In addition to the explanatory variables and control variables 28 dummies for the years 1979 to 2006 and 49 Fama & French (1997) industries dummies are used to control for annual and industry fixed effects in regressions (1) to (3). The controlling for fixed effects is due to the historically unequal distribution of M&As because of merger waves in different industries caused by effects not considered in the regression equations (1) to (3) (Moeller et al. (2005), Harford (2005)). To test the changes in the characteristics the regression equation (1) is estimated for the full data set (See Table 6). The truncated data sets of the first bids and the sixths and later bids are used in regressions (2) and (3) (See Table 6).

In the estimation of probit regression equation [1] the potential problem of heteroscedasticity caused by a relation between the bids or acquisitions of the same bidding company is controlled by clustering the regressions' residuals on the level of the bidding company to obtain robust standard errors (Williams (2000), Froot (1989)). Furthermore the analysis of potential multicollinearity between the independent variables shows that the relative deal size RDS, the tier of the target's advisor TADVISORTIER, REGULATORY and ANTITAKEOVER are correlated. The correlation of 24% to 33% is significant and might cause some multicollinearity.

Finally the multivariate analyses are preceded by the analysis of potential outliers. The continuous variables such as TobinsQ or the relative deal size RDS are winsorized at the upper and lower 1% percentiles. After the univariate analysis of outliers the multivariate outlier analysis is done with the Mahalanobis Distance D^2 measure (Hair et al. (1998), Bar-Hen & Daudin (1995), Mahalanobis (1936)). The Mahalanobis Distance D^2 measure is used, because an acquisition or bid might not be identified as an outlier with respect to each individual variable. The extreme combination of two or more variables however might move the observation beyond the sphere of the multivariate normal distribution focused around the centroid. The centroid is the focal point of the average combination of the variables, the representative average observation or M&A. In a two dimensional space with two variables the centroid is a point and the sphere a circle of a bivariate normal distribution of the two variables. The Mahalanobis Distance D^2 measure rescales the variables, continuous and discrete ones, such that the distance of the values of the variables to the centroid becomes measurable and comparable on a common scale. For the probit regression (1) to (3) 0 deals are excluded at the 0.1% confidence level.

The probit regression [1] is used to calculate the inverse mills ratio 1 that is added to the structural probit regression to test hypothesis 3 to control for the first selection bias that the particular advisor choice is observable only in those transactions in which the acquirer decided to employ an investment bank as advisor. The second selection bias arises as the influence of the advising investment bank's industry expertise and access to the acquirer's private information can be observed only for those banks that have been chosen as advisors, which is modeled with probit regression [2]. The inverse mills ratio 1 from selection equation [1] is calculated according to the selection model of Poirier (1980) and Vella (1998) with the detailed calculations being shown in the statistical appendix.

In table 6 the estimation of probit regression [1] shows that the more complex the transaction is with higher transaction and contracting costs as well as a higher informational asymmetry the more likely is the acquirer hiring an investment bank. If the target employs a bank, the target uses anti-takeover measures, has a pending litigation against it, the deal involves regulatory issues and crosses borders, and the acquirer or the target, or both, are high-tech firms and the target is relatively large, the acquirer has an ownership stake in the target and a higher free cash-flow and a larger set of investment opportunities the probability of the acquirer employing a bank as advisor increases. The results are expected given the prior findings of Servaes & Zenner (1996), Ahern (2008) and Kale et al. (2003). On the other hand an increasing acquisition experience of the acquirer reduces the probability of the transaction being advised.

A large influence on the probability to employ an advisor has the target's advisor choice. A one standard deviation increase in the variable TADVISORTIER increases the likelihood to hire an advisor by 12.40 percentage points (=0.1721 x 0.7207) from 23.52% to 35.92% or relatively by 52.72% (= 12.40% / 23.52%) (See Tables 3D & 6(1)). Similarly the other proxies for the transaction's complexity increase the probability to use an advisor by 1 to 5 percentage points if the variables increase by one standard deviation around the mean. The largest effect has the target's relative size and the size of the acquirer. The relative size of the target increases the advisor employment probability by 9.67 percentage points (= 0.0449 x 2.1526) to 33.19% (See Tables 3D and 6(1)). On the other hand changes of one standard deviation around the mean of the acquirer's acquisition experience over the last three years reduce the advisory probability by 2.71 percentage points (= -0.0087 x 3.1204) (See Tables 3C and 6(1)). The discrete changes of the probability to employ an advisor are relatively large given the changes in the transaction's complexity and informational asymmetry.

To sum it up a higher complexity of the acquisition or bid with increasing transaction costs and informational asymmetry as well as contracting costs increases the likelihood of the employment of a bank as advisor (See Table 6). Compared to the first bid and the full sample in the sixth and later bids with a larger complexity are not more or less likely to be advised. However, as in the univariate analysis the later transactions are more complex such that these transactions are more likely to be advised by more experienced banks.

6.2 The probit regression to test hypothesis 2 of the particular advisor choice

To test hypothesis 2 that the choice of the particular investment bank as advisor depends on the bank's industry expertise in the acquirer's and target's industries as well as its access to the acquirer's private information is modeled with an extended matching model bases on Chang (2008) and shown in table 7.

Insert Table 7 here

Similarly to Chang (2008) and Asker & Ljungqvist (2008) and Ljungqvist et al. (2006) each M&A is matched with each bank of the SDC M&A universe, approximated by sample A, in each year to get all possible acquisition-bank matches. The winning matches in which a bank is the advisor are coded 1, while the losing matches in which the bank is not an advisor are coded 0. As 9,631 acquisitions are advised and each year 16 to 337 investment banks appear in the SDC M&A universe 2,539,315 possible acquisition-advisor pairs exist. 10,929 winning matches of acquisition-bank pairs are given. The number of 10,929 possible winning matches is greater than the number of advised acquisitions or bids, because in some M&As more than one investment bank advised the acquirer with each advisor having his own industry expertise and advisory relationship strength with the acquirer (See Table 1C).

The dependent variable is AADVISOR that is coded 1 for a winning match and 0 for a losing match. For each transaction 16 to 337 dummies AADVISOR are given (See Tables 1C, 2A & 3A). The independent variables model the banks' industry expertise $IE_{i,k,t}$ and their access to the acquirer's private information $I_{i,B,t}$. The variables are therefore IEDA, IEDT, and ARSD (See Tables 2B & 3B). The past performance $PP_{i,B,t}$ of banks acting as advisors in previous M&As of the same bidder are modeled with the variables PASTACAR, PASTCOMPLETED and PASTRESOLSPEED (See Tables 2B & 3B). Finally hypothesis 2 becomes regression equation [2] when substituting the industry expertise $IE_{i,k,t}$ and the access to the private acquirer information $I_{i,B,t}$ with the past performance variables $PP_{i,B,t}$, which is

$$P(AADVISOR_{i,j,t}=1)=f(IE_{i,k,t},I_{i,B,t},PP_{i,B,t}) \quad [2]$$

Similarly to the estimation of probit regression equation [1] the potential problem of heteroscedasticity caused by a relation between 16 to 337 observations of the same bids or acquisitions of the same bidding company, one observation for each bank in the SDC M&A universe, is controlled by clustering the regressions' residuals on the level of the bidding company to obtain robust standard errors (Williams (2000), Froot (1989)). The correlation analysis of the investment banks' characteristics shows that the measures of the industry expertise are highly correlated. The inclusion of the industry expertise in the acquirer industry and in the target industry in probit regression [2] has to be taken with caution as multicollinearity might arise. In the second probit regression [2] the multivariate outlier analysis for the data set of 2,539,315 deal-advisor pairs with respect to the 6 independent variables reveals that at the 0.1% confidence level 0 outliers are given.

The estimation of probit regression [2] is used to calculate inverse mills ratio 2 that is added to the structural probit regression [3] to control for the second selection bias. The second selection bias arises as the influence of the chosen banks' industry expertise and access to the acquirer's private information can be observed only for those banks that are actually chosen as advisors (Poirier (1980), Vella (1998)). The detailed calculation of the inverse mills ratio 2 is shown in the statistical appendix.

The estimates of the second probit regressions [2] in table 7 show in accordance with hypothesis 2 that the bank specific characteristics are of significant relevance for the advisor choice. The industry expertise in the acquirer and target industry, advisory relationship strength and the proxies for the bank's past performance (Rau (2000), Kale et al. (2003)) are all positively correlated with the probability of the bank to be chosen as advisor by the acquirer.

The coefficients show that the acquirer industry and target industry expertise coefficients together have the same influence on the advisor choice as the target industry expertise by itself. Given the high correlation between the industry expertise in the acquirer's industry and the target industry the probit regressions are also run with the target industry expertise only. The expertise in the target industry is of greater significance than the expertise in the acquirer's industry. Information regarding the possible targets and their competitive environment are less accessible by the bidding company than information about its own industry (See Table 7(2)).

The discrete changes of the overall probability of 0.43% of a bank of the SDC M&A universe to be chosen as advisor increases by 0.23 percentage points (= 0.0307 x 0.0757) to 0.66% for a one-standard-deviation increase of the acquirer industry expertise and by 0.20 percentage points (= 0.0273 x 0.0725) to 0.63% for a one standard-deviation increase of the target industry expertise (See Tables 3B and 7(1)). When using the target industry expertise only as explanatory variable it has a discrete effect of 0.40 percentage points (= 0.0546 x 0.0725) on the advisor choice probability when the target industry expertise increases by one standard deviation around the mean (See Tables 3B and 7(2)). When controlling for the past returns of a deal of the same bidder the bank advised the effect is small. A one standard deviation increase in the past returns PASTACAR increases the probability of the bank to be the advisor by 0.008 percentage points (= 0.0022 x 0.0373) to 0.438% (See Tables 3B and 7(1)). It follows that the past performance is rather irrelevant for the advisor choice while modeling the industry expertise directly.

The familiarity of the investment bank with the acquirer has a relative large effect on the probability that the bank is selected as advisor. An increase of one standard deviation of the bank's familiarity with the acquirer relative to other former M&A advisors increases its probability to be chosen by 0.74 percentage points (= 0.0498 x 0.1477), or relatively by 172% (=0.74%/0.43%), to 1.17% (See Tables 3B and 7(1)). The relatively large change in the probability to be chosen as advisor indicates empirically why banks have strong incentives to build advisory relationships with acquirers while competing fiercely for M&A advisory mandates (Anand & Galetovic (2006), Chemmanur & Fulghieri (1994)).

6.3 The probit regression model to test the influence of the advisor choice on the returns (hypothesis 3)

The last regression equation is used to test hypothesis 3 that the advising investment bank's industry expertise and access to the acquirer's private information in the previous M&A has a positive effect on the acquirer's returns and M&A performance. The dependent variable CAR (-1, 1) are the announcement returns from one day before to one day after the acquisition (See Tables 2A & 3A). The independent variables used to approximate the characteristics of the bidding company, the advising investment bank and the acquirer's industry are similarly to probit regression equations [1] and [2] IEDA, IEDT, ARSD, ROA, ITobinsQ, TobinsQ, IS and DEALS3YEARS (See Tables 2B, 2C, 3B, 3C, 6 & 7).

Insert Table 8 here

The variable RELREP is used because the relative reputation of the acquirer's advisor in comparison to the target's advisor has been shown to have a positive and significant correlation with the acquirer's returns (Kale et al. (2003)). Similarly the variables TADVISOTIER and MS are used to model the reputation and rankings of the advising investment banks (Kale et al. (2003), Rau (2000)). These variables are included in regressions 8(4) and 8(5) to check whether they still have explanatory power while approximating the chosen advisor's expertise more directly.

Controlling for potential agency conflicts, such as managerial empire building, and the advising bank's certification role is necessary. The certification effect of the advising investment bank to indicate the value of the acquisition to the shareholders is modeled using the reputation proxy MS (Rau & Rodgers (2002)). Particularly large investment banks have an incentive to advise profitable acquisitions to earn the advisory fees and to extend and preserve their advisory relationships with the acquirer (Anand & Galetovic (2006), Chemmanur & Fulghieri (1994)). The banks want to avoid being involved in agency conflicts between the management and the shareholders that might lead to value destroying acquisitions to safeguard their reputation (Rau (2000), Rau & Rodgers (2002), McLaughlin (1990, 1992)).

A larger investment opportunity set is expected to have a positive influence on the returns. The investment opportunities $\Omega_{B,k,t}$ are modeled with TobinsQ and the size of the acquirer's industry IS (See Tables 2C & 3C). The profitability of the bidding company is measured by ROA (See Table 2C & 3C). The size of the set of investment opportunities and profitability of the acquirer's industry are also measured. The average industry level of debt is controlled with the variable ILEVERAGE (See Table 2C and 3C). The average Tobin's Q of companies in the industry and their profitability are measured by ITobinsQ and IROA (See Tables 2C and 3C). Finally the regression equation [3] to test hypothesis 3 together with the transaction variables is

$$E(CAR\,(-1,1)_{j,t}) = f(IE_{i,k,t}, I_{i,B,t}, \Omega_{B,k,t}, \Delta I_{j,t}, TC_{j,t}, CC_{j,t}) \; [3]$$

The selection biases caused by the fact that the influence of the chosen advising bank's industry expertise and access to the acquirer's private information on the returns is observable only for the chosen advisors in those deals in which the acquirer decided to employ a bank as advisor is corrected by adding the inverse mills ratios 1 and 2 calculated from the estimated probit regressions [1] and [2] shown in tables 6 and 7 (Poirier (1980)). As at least one variable in the structural probit regression [3] must be different from the variables in the selection equations [1] and [2] the industry variable IROA and ILEVERAGE are used (Wooldridge (2002)).

Given that an acquirer has several bids or acquisitions in his acquisition sequence the standard errors are clustered on the level of the bidding company (Williams (2000), Froot (1989)). The correlation analysis of the independent variables shows that the bank variables IEDT, IEDA and

MS are highly correlated. Finally the multivariate outlier analysis for regression equation [3] shows that for the 10,929 deal-advisor pairs used to test hypothesis 3 no observations is identified as an outlier at the 0.1% confidence level. Not for all transactions are the CAR (-1, 1) value weighted available.

The empirical estimation of equation [3] shows that the industry expertise of the bank chosen as advisor has a significantly positive effect on the returns. The industry expertise in the target's industry is more important than the expertise in the acquirer's industry (See Table 8). The regressions (1) to (3) in table 8 show that the selection bias is significant with respect to the measurement of the influence of the advisor's expertise on the returns. Without correcting for the selection bias the observation is made that the employment of a familiar advisor has a negative effect on the returns, shown in table 8(3), similarly to the observations in previous research (e.g. Saunders & Sirinivasan (2001), Bau & Edmans (2011)). Controlling for the selection bias the observation of the industry expertise of the advisor being positively correlated with the returns is made, shown in regression (2), (4) and (5) in table 8. Controlling for the selection bias is economic significant for the estimation of the influence of the bank's industry expertise on the acquirer's acquisition returns.

Besides the advisor characteristics the acquirer and industry characteristics approximating the acquirer's acquisition experience and his investment opportunities have a positive effect on the returns as well. The more investment opportunities are available in the industry, approximated by ITobinsQ, the higher are the returns as more profitable acquisitions can be made (See Table 8(4) & 8(5)). The same holds for the industry's average profitability approximated with IROA. These observations are in line with the neoclassical theory and the empirical results of Klasa & Stegemoller (2007) of more profitable acquisitions being made in industries with better investment opportunities. The measures of the size of the investment opportunities and profitability on the acquirer's individual level are slightly negatively correlated with the industry level variables and thus insignificant or small and negative (See Table 8(4) & 8(5)). The significant inverse mills ratios 1 and 2 in regressions (1), (2) and (5) show that the selection biases also matter for the measurement of the correlation of the investment opportunities and profitability of the acquirer's industry with the acquirer's returns (See Table 8).

Replicating the indirect measures of the acquirer's and the target's advisors' reputation TADVISORTIER is negatively correlated with the acquirer's returns similarly to Kale et al. (2003) (See Table 8(4) and 8(5)). The relative reputation RELREP has no significant influence on the returns, which is different to the positive correlation that Kale et al. (2003) observed. The difference however is likely to be caused by the much larger sample of acquisition-advisor pairs from 1979 to 2006 compared to the sample of 324 successful tender offers from 1981 to 1994 of Kale et al. (2003). The market share MS of the acquirer's advisor has a significantly negative influence, albeit economic small, on the returns similarly to Rau's (2000) observation (See Table 8(5)). The market share MS from the SDC Top-50 League Tables is significantly positively correlated with the more direct measure of the bank's industry expertise IEDA and IEDT while adding little explanatory power.

IEDT as a measure of the industry expertise is significantly positively correlated with the acquirer's returns when controlling for the transaction, acquirer and industry characteristics. A one standard deviation increase in the acquirer's advisor's industry expertise in the target's industry IEDT increases the average return CAR (-1, 1) from 0.80% by 0.38 (=0.0530 x 0.0725) to 0.48 percentage points (=0.0659 x 0.0725) to 1.18% or 1.28%, or relatively by 48% (=0.38%/0.80%) to 60% (=0.47%/0.80%) (See Tables 8(4), 8(5) & 3A). The industry expertise of the advising investment bank has an economic significant positive correlation with the acquirer's returns.

The controlling of the transaction characteristics leaves the inverse mills ratios insignificant. The deal characteristics, omitted for brevity, have the expected signs, while tender offers, majority or controlling acquisitions and mergers of equals and the acquisition of or bidding for relatively large targets are associated with higher announcement returns (See Table 8(4) & 8(5))[5].

Finally the controlling for the selection biases is important for the measurement of the correlation of the advising bank's industry expertise and the acquirer and industry characteristics with the acquirer's announcement returns. The direct assessment of the investment banks' industry expertise, their access to industry information about potential acquirer-target matches and their M&A advisory experience, shows that the industry expertise has an economic significant positive correlation with the announcement returns.

6.4 The probit regression model to test the influence of the advisor choice on the resolution speed

[5] Table 8 including the control variables for the deal characteristics is available online in the appendix at http://voget.bwl.uni-mannheim.de/index.php?id=45 .

Similarly to the analysis of the returns the employment of a bank with a higher industry expertise is positively correlated with a longer time until completion or withdrawal of the bid (See Table 9).

Insert Table 9 here

However, the more experienced investment banks are hired in transactions that are more complex. The deal characteristics mostly determine the complexity of the M&A[6]. Mergers, the payment with stock, mergers of equals, hostile takeovers and multiple bidders make the transaction more complex. The higher complexity increases the time needed to carry out the acquisition or merger. An advising investment bank on the target's side reduces the time to resolve the transaction as the target's management receives professional support similar to the advised acquirer to carry out the transaction. Tender offers and majority acquisition appear to be easier to carry out and take less time to be completed or withdrawn. The advisory relationship strength has no effect when controlling for endogeneity by adding the inverse mills ratios shows in 9(2) and 9(3).

6.5 The probit regression model to test the influence of the advisor choice on the completion probability

The industry expertise has no influence on probability to complete a transaction, but the familiarity with the acquiring company (See Table 10). More complicated transactions such as mergers, diversifying acquisitions, hostile acquisitions, bidding contests and the acquisition or bidding for relatively larger targets are less likely to be completed successfully[7]. On the other hand tender offers are more likely to be completed with a relatively higher reputation of the advising investment bank compared to the target's advisor being helpful as well. Again the endogeneity matters as the inverse mills ratio 1 is statistically significant.

Insert Table 10 here

6.6 The probit regression model to test the influence of the advisor choice and transaction characteristics on the advisor fees

In table 11 it can be seen that more reputable investment banks more familiar with the bidding company receive higher advisor fees. Given the empirical observation that a higher industry expertise, positively correlated with the reputation, and familiarity with the bidding bank are

[6] Table 9 including the control variables for the deal characteristics is available online in the appendix at http://voget.bwl.uni-mannheim.de/index.php?id=45 .

[7] Table 10 including the control variables for the deal characteristics is available online in the appendix at http://voget.bwl.uni-mannheim.de/index.php?id=45 .

associated with higher returns in table 8 a compensation for the bank's more skilled advisory services seems appropriate.

Insert Table 11 here

The advisor fees are driven by the transaction characteristics. The more experienced and skilled investment banks advise the more complex transactions (See Table 4 & 5). Controlling for the transaction characteristics the industry expertise is no longer positively correlated with the advisor fees while the advisory relationship strength still is. The empirical observation of more familiar banks receiving higher fees is similar to the results of Saunders & Sirinivasan (2001).

Particularly cross-border transactions, mergers of equals, diversifying acquisitions and the payment with stock are associated with higher fees[8]. Higher advisor fees appear to be paid by serial acquirers who make six or more acquisitions, because the dummy SIXTH is positively correlated with the advisor fees as well as the profitability measure ROA and the acquirer's leverage. Similarly to the previous regressions the selection bias matters as the inverse mills ratios are significant. The high R^2 shows that the acquirer, advising bank and transaction characteristics explain a larger part of the variation in the advisor fees.

7. The sensitivity analysis of simplifying the Poirer (1980) selection model into a two-stage ordered probit Heckman (1976, 1979) selection model

The simplification of the Poirier (1980) selection model into a two-stage ordered probit selection model (Heckman (1976, 1979), Vella (1993, 1997, 1998)) provides similar observations as the separate estimation of the two selection equations [1] and [2]. The selection equations of the decision whether to hire an advising investment bank and which one in particular are simplified to the decision of the type of advisor, either unadvised, non-bulge-bracket bank or a bulge-bracket bank (See Table 12). The acquirers with greater investment opportunities and a higher free cash flow to finance these opportunities are more likely to employ a bank as advisor.

Insert Table 12 here

More complicated transactions with higher transaction and contracting costs as well as informational asymmetries are more likely to be advised by investment banks. With respect to the structural regressions that incorporate the inverse mills ratio from the first step selection

[8] Table 11 and 12 including the control variables for the deal characteristics are available online in the appendix at http://voget.bwl.uni-mannheim.de/index.php?id=45 .

ordered probit regressions the results are similar to the observations in table 8 (See Table 13). The inverse mills ratios are calculated from the selection regressions in table 12. The detailed calculations of the inverse mills ratios are shown in the statistical appendix.

Insert Table 13 here

A greater industry expertise in the target's industry is associated with higher announcement returns for the acquirer if he employs a bulge-bracket bank. M&As in industries with a higher average profitability measured by IROA and greater investment opportunities measured by ITobinsQ are also associated with higher announcement returns (See Table 13). The transaction characteristics have the same signs as in the structural regression in table 8. It follows that the empirical observations of the simplified analysis are comparable. The modeling of the selection of the individual bank as advisor in tables 7 and 8 however shows in more detail the positive association of a higher industry expertise with returns.

8. The "what if" analysis of the returns if another type of advisor had been hired

Besides the analysis of the effect of the choice of the financial advisor on the returns and performance in serial acquisitions while considering the selection biases the question arises what the returns had been if another type of financial advisor had been hired. This analysis extents the analyses of Golubov et al. (2010) by not only considering the choice between non-bulge-bracket banks and bulge-bracket banks but also the option not to employ any financial advisor to do the M&A with an in-house acquisition team (Servaes & Zenner (1996)). In the case of not employing a financial advisor the bidder saves the advisory fees.

The "what if" analysis is based on the ordered probit two stage selection model of Heckman (1976, 1979) and Vella (1993, 1998) shown in tables 12 and 13. The coefficients of the linear estimations (4), (5) and (6) in table 13 are used to estimate the transaction and the acquirer with their characteristics for alternative advisor choices. For instance if an M&A is unadvised, its returns are estimated using the coefficients of (5) and (6) as if a non-bulge-bracket bank or a bulge-bracket bank had been employed. Each year the SDC Top-50 M&A League Tables include 50 to 51 investment banks, with the top-10 banks being defined as bulge-bracket banks. All other banks and those appearing in the SDC M&A universe but not in the SDC League Tables are defined as non-bulge-bracket banks. The option not to employ a financial advisor is added as additional alternative "advisor" choice. For the unadvised M&A the alternative return if a non-bulge-bracket bank had been employed is the average of the estimated returns using the coefficients from the regression estimation (5) for each of the SDC M&A universe non-bulge-bracket banks that differ in their industry expertise and familiarity with the acquirer. Similarly the unadvised M&A's alternative return for the potential employment of a bulge-bracket bank as advisor is the average of the estimated returns using equation (6) for each of the 10 bulge-bracket banks with their individual industry expertise and acquirer-advisor relationship strengths as well as the transaction's and acquirer's characteristics.

The hypothetical returns of the alternative types of financial advisors are averaged over the advisor type. For each deal three returns are given, two alternative ones for the two alternative advisor choices and the real return. These three returns in the sample of 40,961 acquisitions or bids are used to calculate the improvement that the two alternative types of financial advisor offer compared to the real return. With the differences in the hypothetical and real returns one can see whether the choice of an alternative financial advisor would have been an improvement or resulted in worse announcement returns for the bidding company. The hypothetical returns are estimated using the regression coefficients that are statistically significantly different from 0, the covariance between the residuals and the inverse mills ratios from the two-stage ordered probit selection model shown in Table 13.

It follows that for each unadvised M&A the expected hypothetical return if it had been advised by a bulge-bracket bank is $E\left[y_{3i} \mid unadvised = 1\right] = E\left[X_i'\beta_3 + u_{3i} + \text{cov}\left(u_{3i}, \varepsilon_1\right) \times \lambda_1\right]$ and if the unadvised deal had been advised by a non-bulge-bracket bank the expected return is $E\left[y_{2i} \mid unadvised = 1\right] = E\left[X_i'\beta_2 + u_{2i} + \text{cov}\left(u_{2i}, \varepsilon_1\right) \times \lambda_1\right]$. The return improvements of the alternative financial advisor choices for the unadvised M&A are the differences between the real return and the hypothetical returns, thus $E\left[y_{3i} \mid unadvised = 1\right] - y_{1i}$ and $E\left[y_{2i} \mid unadvised = 1\right] - y_{1i}$.

Similarly for a non-bulge-bracket bank advised deal the hypothetical return if it had been advised by a bulge-bracket bank is $E\left[y_{3i} \mid non\_bu\lg e\_bracket = 1\right] = E\left[X_i'\beta_3 + u_{3i} + \text{cov}\left(u_{3i}, \varepsilon_2\right) \times \lambda_2\right]$. The hypothetical return for a non-bulge-bracket bank advised deal is for the alternative not to use any advisor $E\left[y_{1i} \mid non\_bu\lg e\_bracket = 1\right] = E\left[X_i'\beta_1 + u_{1i} + \text{cov}\left(u_{1i}, \varepsilon_2\right) \times \lambda_2\right]$. The return improvements of the alternative financial advisor choice are thus $E\left[y_{3i} \mid non\_bulge\_bracket = 1\right] - y_{2i}$ and $E\left[y_{1i} \mid non\_bulge\_bracket = 1\right] - y_{2i}$.

Finally for a bulge-bracket bank advised bid or acquisition the hypothetical returns if it had been advised by a non-bulge-bracket bank or in-house M&A team are $E\left[y_{2i} \mid bulge\_bracket = 1\right] = E\left[X_i'\beta_2 + u_{2i} + \operatorname{cov}\left(u_{2i}, \varepsilon_3\right) \times \lambda_3\right]$ and $E\left[y_{1i} \mid bulge\_bracket = 1\right] = E\left[X_i'\beta_1 + u_{1i} + \operatorname{cov}\left(u_{1i}, \varepsilon_3\right) \times \lambda_3\right]$. The improvements for the bulge-bracket bank advised transactions are $E\left[y_{2i} \mid bulge\_bracket = 1\right] - y_{3i}$ and $E\left[y_{1i} \mid bulge\_bracket = 1\right] - y_{3i}$.

Insert Table 14 here

The results of the real returns, the hypothetical returns that are estimated and the improvements are shown in table 14. In table 14 it can be seen that the choice of a non-bulge-bracket bank or an in-house acquisition team in a transaction that is advised by a bulge-bracket bank would have caused worse returns. For an unadvised transaction employing an external financial advisor, a non-bulge-bracket or bulge-bracket bank, would have improved the returns of the bidding company only if a bulge-bracket bank had been employed. The employment of a non-bulge-bracket bank had resulted in worse returns. However, not employing a financial advisor at all in the case of non-bulge-bracket banks advised deals would not have worsened the returns. In the case of M&As advised by non-bulge-bracket banks choosing a bulge-bracket bank would have increased the returns as well. It follows from the results shown in table 14 that the employment of a more experienced bulge-bracket bank results in higher returns. The industry expertise and the familiarity with the acquirer correlate positively with the rank of the investment bank. The employment of a non-bulge-bracket bank had resulted in mixed returns and it is not clear whether non-bulge-bracket banks provide improvements compared to not employing a bank as advisor at all, assuming that the deal can be completed without external advice. The regression coefficient of the industry expertise of non-bulge-bracket banks in table 13 is not significantly different from 0 such that the non-bulge-bracket banks' industry expertise has no positive effect on the estimated hypothetical returns. The results match the results of Golubov et al. (2010) that bulge-bracket banks are able to advise all kinds of transactions compared to non-bulge-bracket banks or unadvised deals.

9. Conclusion

The empirical analysis shows that the unification of the neoclassical theory with the analysis of the role of investment banks as M&A advisors in acquisition sequences reveals the value of the advisory services that the banks provide. The observations of the industry expertise of the chosen advising investment banks being positively correlated with the returns of the acquirer is obtained by directly modeling the bank's M&A advisory expertise. The empirical results of this study differ from the mixed results of previous studies because of the replacement of the M&A market share MS as an approximation of a bank's advisory reputation and thus quality by the more direct measures IEDT and IEDA of the industry expertise.

The consideration of the endogeneity in the advisor choice, that bulge-bracket banks are matched with the largest and most complex transactions and non-bulge-bracket banks with the smaller and less complex ones, is necessary as otherwise the smaller returns in larger and more complex transactions are attributed to the bank. The bulge-bracket banks however have a larger industry expertise than the non-bulge bracket banks. Controlling for the endogeneity related to two selection biases and the transaction, acquirer and industry characteristics a higher industry expertise is positively associated with returns. Nevertheless a large part of the variation in the announcement returns is unexplained as the R^2 of the returns regressions of about 10% shows. Further research is needed to explain the announcement returns that capture the acquisition's or merger's net present value to isolate the effect of the advising bank's expertise and familiarity with the bidder.

The "what if" analysis that extends the switching model of Golubov et al. (2010) who used the model of Fang (2005) by considering the option not to employ an advising bank at all, besides a non-bulge-bracket or bulge-bracket bank, reveals the higher returns that experienced banks provide. Given that the advisory services of bulge-bracket banks would have resulted in higher returns the higher advisor fees they receive for their services seem to be appropriate.

Finally the matching of bulge-bracket banks with the largest and most complex transaction that require a lot of expertise and information about the acquirer and target and their industries is efficient. The hierarchical structure in the investment banking market observed and theoretically modeled by Anand & Galetovic (2006) and Chemmanur & Fulghieri (1994) is thus efficient when considering the investment banks as financial intermediaries that match the acquirers with the best fitting and most profitable targets.

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11. Appendix

In its estimation of the selection model of Poirier (1980) to control for endogeneity the inverse mills ratios are calculated from selection equations [1] and [2] and insert into the structural equation [3] of the M&A returns (Poirier (1980) and Vella (1998)). The inverse mills ratios under the assumption of the two selection equations [1] and [2] being related are $\lambda_1 = \frac{\varphi\left(X_j'\beta_1\right)\phi\left(X_j'\beta_2 - \rho_{u_1,u_2}X_j'\beta_1\right)\Big/\left(1-\rho_{u_1,u_2}^2\right)^{1/2}}{\phi^b\left(X_j'\beta_1, X_j'\beta_2; \rho_{u_1,u_2}\right)}$ and $\lambda_2 = \frac{\varphi\left(X_j'\beta_2\right)\phi\left(X_j'\beta_1 - \rho_{u_1,u_2}X_j'\beta_2\right)\Big/\left(1-\rho_{u_1,u_2}^2\right)^{1/2}}{\phi^b\left(X_j'\beta_1, X_j'\beta_2; \rho_{u_1,u_2}\right)}$ (Poirier (1980), Vella (1998)). ρ_{u_1,u_2} is the correlation between the error terms u_1 and u_2 of regression equations [1] and [2] while $\phi^b\left(X_j'\beta_1, X_j'\beta_2; \rho_{u_1,u_2}\right)$ refers to the bivariate normal distribution. $X_j'\beta_1$ is the linear projection of equation [1] and $X_j'\beta_2$ is the linear projection of equation [2].

In the sensitivity analysis the inverse mills ratios for each of the three outcomes of the two-stage ordered probit selection model are calculated and added in the second stage structural regression of the returns of the M&A with one regression for each of the three outcomes from the first stage (Heckman (1976, 1979), Vella (1992, 1993, 1998), Main & Reilly (1993), McKelvey & Zavoina (1975)). The inverse mills ratio in the structural regression for outcome 1 when *ADVISORCHOICE=1* is $\lambda_1 = \frac{-\varphi(\mu_1 - X_j'\beta)}{\phi(\mu_1 - X_j'\beta)}$ with μ_1 being the cut-off point between outcome 1 and 2 of the normal distribution of the outcomes. For the regression equation with outcome 2 of *ADVISORCHOICE =2* it is $\lambda_2 = \frac{\varphi(\mu_1 - X_j'\beta) - \varphi(\mu_2 - X_j'\beta)}{\phi(\mu_2 - X_j'\beta) - \phi(\mu_1 - X_j'\beta)}$ with μ_2 being the cut-off point between outcome 2 and 3. For the regression equation of outcome 3 of *ADVISORCHOICE =3* the inverse mills ratio is $\lambda_3 = \frac{\varphi(\mu_2 - X_j'\beta)}{1 - \phi(\mu_2 - X_j'\beta)}$.

12. Tables

Table 1: Data preparation and sample statistics

The sample is taken from the SDC Mergers & Acquisitions database. The sample includes US targets only. The deals included are M&As (1, 2), spinoffs & splitoffs (4), tender offers (5), minority stake purchases (10), acquisitions of remaining interest (11), and privatizations (12). The initial sample of 208,654 deals from 01/01/1979 to 12/31/2008 is reduced by missing Compustat data as well as incomplete variables. The sample includes only M&As of corporate acquirers as well as stake purchases. Most deals without Compustat data are private acquirers. The final sample includes deals from 01/01/1979 to 12/31/2006. Panel B includes the major statistics of the acquisition sequences. Panel C reports the distribution of the bids and acquisitions over time, the number of advised bids/acquisitions per year, the number of investment banks as advisors included in the SDC M&A sample, the possible acquisition-bank matches, the actually chosen acquisition-advisor matches, and the missing matches as the acquirer's advisor is not included in the SDC M&A sample.

Panel A: Observation elemination

Steps in the Process	deals excluded	M&As
1. The total SDC M&A sample		208.654
2. Excluding self tenders, recapitalisations and repurchases	20.328	188.326
3. Excluding "Creditors", "Investor", "Investors", "Investor Group", "Shareholders", "Undisclosed Acquiror", "Seeking Buyer", and "Employee Stock Ownership Plan"	21.548	166.778
4. Excluding deals with status of "Unknown Status", "Rumor", "Discontinued Rumor", "Intended", "Intent withdrawn", and "Seeking Target"	11.083	155.695
5. Excluding acquisitions/bids with undisclosed transaction values	84.336	71.359
6. Excluding individual and financial acquirers	5.660	65.699
7. Excluding bids in which the target is the same company as the acquirer	38	65.661
Sample A before the merging processes, used to compute the industry experience and acquirer-advisor relationship strength variables		65.661
8. Excluding acquisitions/bids without Compustat data for the acquirer	24.700	40.961
Sample B for the first step advised/unadvised analysis		40.961
9. Excluding acquisitions/bids without CRSP data for the acquirer	5.706	35.255
Sample C for the third step returns analysis		35.255

Panel B: Major acquisitions series characteristics in the final sample B

Variable	N	Mean	Median	Std.Dev.	Min	Max
Number of acquisitions/bids in the final sample	40.961	---	---	---	---	---
Number of acquirers/bidders in the final sample	13.683	---	---	---	---	---
Acquisitions per acquirer and sequence	---	3,0	2,0	4,1	1	100
Days between acquisitions/bids	---	521,2	224,0	806,7	0	9289
Days between the 1st and 2nd bid in SDC	---	795,7	378,0	1094,4	0	9289
Days between the 2nd and 3rd bid in SDC	---	642,9	320,0	867,2	0	8141
Days between the 3rd and 4th bid in SDC	---	525,2	267,0	720,6	0	7309
Days between the 4th and 5th bid in SDC	---	447,2	215,0	643,9	0	6177
Days between the 5th and 6th and higher bid in SDC	---	299,8	130,0	475,1	0	6419

Table 1 (cont.): Data preparation and sample statistics

Panel C: Time series of acquisitions/bids and possible acquirer-advisor matches

	advised and unadvised bids/acquisitions		acquisition-bank matches					
Year	Bids / Acquisitions	Advised Deals	Banks in the SDC Universe	SDC M&A League Table Banks (#)	Possible Matches	Winning Matches	Losing Matches	Missing Matches
1979	14	10	16	20	160	11	149	0
1980	55	27	45	49	1.215	29	1.186	0
1981	372	84	76	50	6.384	94	6.290	0
1982	525	93	99	50	9.207	103	9.104	0
1983	711	121	110	50	13.310	127	13.183	0
1984	861	151	105	51	15.855	160	15.695	0
1985	391	148	86	50	12.728	165	12.563	0
1986	659	240	133	50	31.920	262	31.658	0
1987	717	211	169	50	35.659	236	35.423	0
1988	767	229	184	50	42.136	253	41.883	0
1989	962	234	214	50	50.076	277	49.799	0
1990	877	150	182	50	27.300	167	27.133	0
1991	1.006	149	184	50	27.416	168	27.248	0
1992	1.294	200	196	51	39.200	213	38.987	0
1993	1.654	297	207	50	61.479	355	61.124	0
1994	2.041	433	265	50	114.745	490	114.255	0
1995	2.015	478	269	50	128.582	519	128.063	0
1996	2.654	573	286	50	163.878	620	163.258	0
1997	3.493	773	337	50	260.501	865	259.636	0
1998	3.525	735	302	50	221.970	821	221.149	0
1999	2.817	729	314	50	228.906	816	228.090	0
2000	2.701	752	289	50	217.328	867	216.461	0
2001	1.801	520	278	50	144.560	607	143.953	0
2002	1.652	408	254	50	103.632	455	103.177	0
2003	1.638	402	260	50	104.520	454	104.066	0
2004	1.815	483	308	50	148.764	571	148.193	0
2005	1.991	524	332	50	173.968	628	173.340	0
2006	1.953	478	322	50	153.916	596	153.320	0
Total / Mean	40.961	9.632			2.539.315	10.929	2.528.386	0

Table 2: Description of variables

This table includes the descriptions of the variables. Panel A includes the definitions of the dependent variables used in the two selection probit regressions and the final structural probit regression of the Poirier (1980) selection model as well as the first stage dependent variable of the rank order of advisory choices for the two-stage odered probit selection model of Heckman (1976, 1979). Panel B includes the explanatory variables of the characteristics of the SDC M&A sample banks that each year represent the sample of possible bidder advisors. The bank characteristics are used in selection equation [2]. Panel C includes the bidder characteristics that are used as explanatory variables in selection regression [1] and the structural regression [3]. Panel D includes the explanatory variables that describe and control for the characteristics of the bids/acquisitions in regressions [1] and [3].

Panel A: Definitions of the dependent variables

Variable	Definition	Source
ADVISED	Dummy (0/1) if the deal is advised on the acquirer's side .	SDC
AADVISOR	Dummy (0/1) for each bank chosen as advisor.	SDC
CAR (-1, 1) value weighted	The CARs from -1 to +1 days around the announcement date are computed with the market model CAPM using the CRSP value weighted index.	CRSP
ADVISORCHOICE	Ordered probit variable of no advisor (1), a non-bulge-bracket bank (2) or a bulge-bracket bank (3) as the bidder's choice of the financial advisor for the first stage in the two-stage ordered probit selection model.	SDC
RESOLSPEED	RESOLSPEED is the time in days from the announcement until the withdrawal or completion of the M&A, ranging from 0 to 730 days.	SDC
COMPLETED	COMPLETED is the dummy (0/1) whether the bank completed the M&A it advised.	SDC
ADVISORFEE	ADVISORFEE is the fee in $mil that the advising bank of the acquirer received for	SDC

Table 2 (cont.): Description of variables

Panel B: Definitions of the bank variables

Variable	Definition	Source
IEDA, IEDT	The variables of the banks' industry expertise are adopted and modified from Chang et al. (2008) and theoretically based on Anand & Galetovic (2006) and Chemmanur & Fulghieri (1994). "IEDT" is the bank's industry expertise by the number of deals in the target's industry . "IEDA" is the bank's industry expertise by the number of deals in the acquirer's/bidder's industry. The industry expertise is normalized to have a ratio between 0 and 1. It is a relative measure compared to the industry expertise of other banks in the industry. The formula for the industry expertise at time t of bank i in industry k measured by the number of advised deals is IEDt,i,k=[(advised_dealst-1,i,k/advised_industry_dealst-1,k)+(advised_dealst-2,i,k/advised_industry_dealst-2,k)+(advised_dealst-3,i,k/advised_industry_dealst-3,k)]/3.	SDC
ARSD	This variable is adapted from Saunders & Srinivasan (2001) and Forte et al. (2007) and theoretically based on Anand & Galetovic (2006) and Chemmanur & Fulghieri (1994). It measures the advisory relationship strength of the bidder and the bank over the last 3 years. "ARSD" is the advisory relationship strength by the bidder's number of deals advised by the bank. The formula for the advisory relationshop strenght at time t of bank i for bidder j measured by the number of advised deals is $ARSD_{t,i,j}$=[($advised\_deals_{t-1,i,j}$/$advised\_bidder\_deals_{t-1,j}$)+($advised\_deals_{t-2,i,j}$/$advised\_bidder\_deals_{t-2,j}$)+($advised\_deals_{t-3,i,j}$/$advised\_bidder\_deals_{t-3,j}$)]/3. The advisory relationship strength is normalized to have a ratio between 0 and 1.	SDC
RELREP	The relative reputation RELREP is the acquirer's bank's market share in the SDC Top-50 M&A League Tables divided by the target's bank's market share.	SDC
MS	The bank's market share in the SDC Top-50 M&A League Tables.	SDC
PASTACAR	PASTACAR is the CAR (-1, 1) value weighted of the bank if it advised the acquirer in a previous M&A. It is the past CAR $(-1, 1)_{i-1}$ multiplied with the dummy if the CAR $(-1, 1)_{i-1}$ is available.	CRSP, SDC
PASTCOMPLETED	PASTCOMPLETED is the dummy (0/1) whether the bank completed the M&A if it advised the acquirer in a previous deal.	SDC
PASTRESOLSPEED	PASTRESOLSPEED is the time in days from 0 to 730 from the announcement to the completion or withdrawal date if the bank advised the acquirer in a previous deal.	SDC

Table 2 (cont.): Description of Variables

Panel C: Definitions of the bidder variables

Variable	Definition	Source
DEALS3YEARS	Number of the bidder's M&As in the preceeding 3 years.	SDC
TobinsQ	Tobin's Q in year t of the M&A of the bidder as [(Book Value of Assets$_{t-1}$+Market Value of Equity$_{t-1}$-Book Value of Equity$_{t-1}$)/Book Value of Assets$_{t-1}$] (Andrade & Stafford (2004).	Compustat
ITobinsQ	ITobinQ is the mean industry Tobin's Q, defined as the average of the industry's companies' Tobin's Q excluding the bidder's Tobin's Q in the year before the M&A. The industries are defined according to Fama & French (1997).	Compustat
FCF	Free cash-flow is defined as [(EBITDA$_{t-1}$-Interest Expense$_{t-1}$-(Income Taxes$_{t-1}$-(Deferred Taxes and Investment Tax Credit$_{t-1}$-Deferred Taxes and Investment Tax Credit$_{t-2}$))-Dividends (Preferred)$_{t-1}$-Dividends (Common)$_{t-1}$)/Book Value of Assets$_{t-1}$] according to Lang et al. (1991).	Compustat
ROA	Return on assets is defined as [Net Income (Loss)$_{t-1}$/Book Value of Assets$_{t-1}$] (Bao & Edmans (2009), Moeller et al. (2004, 2005)).	Compustat
IROA	IROA is the industry return on assets, defined as the average of the industry's companies' ROA excluding the bidder's ROA in the year before the M&A. The industries are defined according to Fama & French (1997).	Compustat
LEVERAGE	Leverage at time t of the deal is defined as [(Long-term Debt$_{t-1}$+Debt in Current Liabilities$_{t-1}$)/Book Value of Assets$_{t-1}$] (Masulis et al. (2005)).	Compustat
ILEVERAGE	ILEVERAGE is the mean industry leverage, defined as the average of the industry's companies' leverage excluding the bidder's leverage in the year before the M&A. The industries are defined according to Fama & French (1997).	Compustat
IS	IS is the industry size of the bidder measured by the number of companies in the bidder's Fama & French (1997) industry in the year before the bid or acquisitions.	Compustat

Table 2 (cont.): Description of Variables

Panel D: Definitions of the Transaction Variables

Variable	Definition	Source
TADVISORTIER	Discrete choice variable of the target's advisor's tier (unadvised (0), non-bulge-bracket (1), bulge-bracket (2)) (Kale et al. (2003)).	SDC
FIRST	Dummy (0/1) if the bid is the first one in the acquisition sequence.	SDC
SIXTH	Dummy (0/1) if the bid is the sixths or later one in the sequence.	SDC
DIVERS	Dummy (0/1) if the target and the acquirer have different primary 2-digit SIC codes.	SDC
MAJORITY	Dummy (0/1) if the bidder seeks a majority ownership share of more than 50% and owns less than 50% before the deal.	SDC
SOMESTOCK	Dummy (0/1) if the deal's financing includes at least some stock.	SDC
MERGER	Dummy (0/1) if deal is a merger (Form=Merger)	SDC
TENDER	Dummy (0/1) if deal is a tender offer (tend=Yes)	SDC
MERGEREQUAL	Dummy (0/1) if deal is a merger of equals	SDC
HOSTILE	Dummy (0/1) if the acquisition is hostile.	SDC
ANTITAKEOVER	Dummy (0/1) if the target has anti-takeover measures (Comment & Schwert (1995)).	SDC
FAMILY	Dummy (0/1) if a family owns more than 20% of the target (Kale et al. (2003)).	SDC
LITIGATION	Dummy (0/1) if the target has a pending litigation / legal issues (Kale et al. (2003)).	SDC
REGULATORY	Dummy (0/1) if the M&A requieres regulatory approval, e.g. from an anti-monopoly commission (Kale et al. (2003)).	SDC
CROSSBORDER	Dummy (0/1) if the bidder is from a country other than the USA (Jong et al. (2008)).	SDC
TOEHOLD	TOEHOLD is the percentage of the target owned by the bidder prior the bid/acquisition (Kale et al. (2003)).	SDC
HIGHTECH	Dummy (0/1) if the target or the bidder or both are high-tech firms (Loughran & Ritter (2004)).	SDC
DIVERSIFICATION	DIVERSIFICATION is the logarithm of the number of SIC codes of the target (Servaes & Zenner (1996), Chang (2008)).	SDC
MULTIPLE	Multiple Bidders is defined as the number of bidders.	SDC
RDS	Relative Deal Size (RDS) is defined as the transaction value divided by the bidder's market value of equity. It is defined as [log((Transaction Value/(1,000,000 x CPI_factor))/(Shares outstanding$_{t-1}$ x Price per Share$_{t-1}$))] (Fuller et al. (2002), Moeller et al. (2004, 2005)). The transaction value is adjusted for inflation with the consumer price index. "CPI_factor" is the consumer price index as of 2006 according to the US Federal Reserve bank.	SDC, Compustat, US Federal Reserve Bank

Table 3: Statistics of variables

This table reports the sample statistics of the bank, bidder and transaction variables. The statistics are reported for those bids/acquisitions for which the data is available. The bank/advisor characteristics for the sample of 40,961 deals of which 9,632 are advised on the bidder's side are those of the lead bank/advisor with the highest market share. The variable AADVISOR is the dependent variable in the sample of all possible bank advisors in the annual SDC M&A universe matched to the 9,632 advised M&As, which is used for the second selection equation in table 7. With 16 to 337 banks in the SDC M&A universe annually 2.539.315 possible matches as observations exist. The variables are described in table 2. The continous variables are winsorized at the upper and lower 1 percentile to exclude outliers.

Variable	N	Mean	Median	Std.Dev.	Min	Max
Panel A: Descriptive statistics of the dependent variables						
ADVISED	40.961	0,2352	0,0000	0,4241	0,0000	1,0000
AADVISOR	2.539.315	0,0043	0,0000	0,0655	0,0000	1,0000
CAR (-1, 1) value weighted	35.255	0,0080	1,0000	0,0892	-0,7276	5,4432
ADVISORCHOICE	40.961	1,3468	1,0000	0,6707	1,0000	3,0000
RESOLSPEED	38.745	76	41	105	0	730
COMPLETED	40.956	0,8954	1,0000	0,3061	0,0000	1,0000
ADVISORFEE	1.660	3,2061	1,3000	5,0873	0,0080	60,0000
Panel B: Descriptive statistics of the bank/advisor variables						
IEDA	9.632	0,0714	0,0501	0,0757	0,0000	0,6048
IEDT	9.632	0,0683	0,0478	0,0725	0,0000	0,6048
ARSD	9.632	0,0515	0,0000	0,1477	0,0000	1,0000
RELREP	6.875	8,3465	1,0000	23,4797	0,0036	376,0000
MS	9.632	10,6004	6,5000	11,7210	0,1000	94,6000
PASTACAR	2.539.315	0,0008	0,0000	0,0373	-0,5147	0,8821
PASTCOMPLETED	2.539.315	0,2690	0,0000	0,4434	0,0000	1,0000
PASTRESOLSPEED	2.539.315	31,8891	0,0000	74,5300	0,0000	730,0000

Table 3 (cont.): Statistics of variables

Panel C: Descriptive statistics of the bidder variables						
Variable	N	Mean	Median	Std.Dev.	Min	Max
DEALS3YEARS	40.961	1,6675	1,0000	3,1204	0,0000	58,0000
TobinsQ	40.961	1,9898	1,3484	2,2416	0,0000	15,8142
ITobinsQ	40.961	0,0052	0,0009	0,0163	-0,0160	0,1256
FCF	40.961	0,0163	0,0421	0,1913	-1,2008	0,2765
ROA	40.961	-0,0119	0,0252	0,2226	-1,4711	0,2678
IROA	40.961	-0,0010	-0,0002	0,0038	-0,0305	0,0030
LEVERAGE	40.961	0,2642	0,2106	0,2627	0,0000	1,4115
ILEVERAGE	40.961	0,0007	0,0001	0,0025	-0,0029	0,0154
IS	40.961	1093,2	884,0	861,4	5,0	2847,0
Panel D: Descriptive statistics of the transaction variables						
TADVISORTIER	40.961	0,4687	0,0000	0,7207	0,0000	2,0000
FIRST	40.961	0,3274	0,0000	0,4693	0,0000	1,0000
SIXTH	40.961	0,2557	0,0000	0,4363	0,0000	1,0000
DIVERS	40.961	0,4331	0,0000	0,4955	0,0000	1,0000
MAJORITY	40.961	0,9452	1,0000	0,2275	0,0000	1,0000
SOMESTOCK	40.961	0,2975	0,0000	0,4571	0,0000	1,0000
MERGER	40.961	0,3642	0,0000	0,4812	0,0000	1,0000
TENDER	40.961	0,0351	0,0000	0,1841	0,0000	1,0000
MERGEREQUAL	40.961	0,0025	0,0000	0,0501	0,0000	1,0000
HOSTILE	40.961	0,0089	0,0000	0,0941	0,0000	1,0000
ANTITAKEOVER	40.961	0,0319	0,0000	0,1756	0,0000	1,0000
FAMILY	40.961	0,0030	0,0000	0,0543	0,0000	1,0000
LITIGATION	40.961	0,0162	0,0000	0,1262	0,0000	1,0000
REGULATORY	40.961	0,2630	0,0000	0,4403	0,0000	1,0000
CROSSBORDER	40.961	0,0792	0,0000	0,2700	0,0000	1,0000
TOEHOLD	40.961	1,6820	0,0000	8,9247	0,0000	62,1000
HIGHTECH	40.961	0,2816	0,0000	0,4498	0,0000	1,0000
DIVERSIFICATION	40.961	0,4838	0,0000	0,5689	0,0000	3,2189
MULTIPLE	40.961	1,0236	1,0000	0,2019	1,0000	8,0000
RDS	40.961	-2,4855	-2,3517	2,1526	-14,8447	9,5422

Table 4: Univariate tests of the dependent, advisor, acquirer, and transaction variables between the bids

Table 4 shows the distribution of the variables over the bids/acquisitions of the acquisition sequences. The last column shows the t-tests with the t-value and difference between the first (1), fifths (5) or sixths and higher bids (6).

Panel A: Distribution of the dependent variables

Variable	bids in the acquisition sequence	FIRST 1	SECOND 2	THIRD 3	FOURTH 4	FIFTH 5	SIXTH 6	All Bids	t-test 1 - 5 = 0	t-test 1 - 6 = 0
ADVISED	Mean	0,2204	0,2426	0,2528	0,2624	0,2453	0,2308	0,2352	-0,0249	-0,0104
	N	13.409	7.024	4.538	3.171	2.344	10.475	40.961	-2,6630[a]	-1,9075[b]
ADVISORCHOICE	Mean	1,3097	1,3421	1,3676	1,3879	1,3746	1,3698	1,3468	-0,0649	-0,0601
	N	13.409	7.024	4.538	3.171	2.344	10.475	40.961	-4,5391[a]	-6,9152[a]
CAR (-1, 1) value weighted	Mean	0,0114	0,0121	0,0100	0,0086	0,0049	0,0015	0,0080	0,0066	0,0100
	N	10.586	5.931	3.992	2.848	2.125	9.773	35.255	2,6945[a]	8,2058[a]
RESOLSPEED	Mean	75,9294	74,5756	75,7244	76,7082	78,6806	76,5838	76,0591	-2,7512	-0,6544
	N	12.679	6.664	4.307	3.029	2.229	9.837	38.745	-1,1157	-0,4702
COMPLETED	Mean	0,8910	0,8963	0,8953	0,8994	0,8907	0,9002	0,8954	0,0002	-0,0093
	N	13.409	7.023	4.537	3.170	2.343	10.474	40.956	0,0330	-2,3170[b]
ADVISORFEE	Mean	2,0888	2,1773	2,4972	3,9627	3,8924	5,0488	3,2061	-1,8035	-2,9600
	N	471	298	213	137	101	440	1.660	-4,1006[a]	-8,8007[a]
BULGE-BRACKET-BANK	Mean	0,0893	0,0995	0,1148	0,1255	0,1293	0,1390	0,1117	-0,0497	-0,0400
	N	13.409	7.024	4.538	3.171	2.344	10.475	40.961	-12,1734[a]	-6,0937[a]
NON-BULGE-BRACKET BANK	Mean	0,1312	0,1431	0,1379	0,1369	0,1160	0,0918	0,1235	0,0151	0,0393
	N	13.409	7.024	4.538	3.171	2.344	10.475	40.961	2,0181[a]	9,5136[a]

[a] p<0.01, [b] p<0.05, [c] p<0.1

Table 4 (cont.): Univariate tests of the dependent, advisor, acquirer, and transaction variables between the bids

Panel B: Distribution of the bank variables

Variable	bids in the acquisition sequence	FIRST 1	SECOND 2	THIRD 3	FOURTH 4	FIFTH 5	SIXTH 6	All Bids	t-test 1 - 5 = 0	t-test 1 - 6 = 0
IEDA	mean	0,0636	0,0679	0,0703	0,0748	0,0775	0,0812	0,0714	-0,0139	-0,0175
	N	2.956	1.704	1.147	832	575	2.418	9.632	-4,0002[a]	-8,6872[a]
IEDT	mean	0,0614	0,0646	0,0691	0,0692	0,0733	0,0774	0,0683	-0,0119	-0,0160
	N	2.956	1.704	1.147	832	575	2.418	9.632	-3,5412[a]	-8,2506[a]
ARSD	mean	0,0000	0,0268	0,0497	0,0634	0,0911	0,1192	0,0515	-0,0911	-0,1192
	N	2.956	1.704	1.147	832	575	2.418	9.632	-27,3624[a]	-29,2702[a]
MS	mean	8,7067	9,3299	10,1128	10,2709	11,4348	13,9570	10,6004	-2,7281	-5,2503
	N	2.956	1.704	1.147	832	575	2.418	9.632	-5,3022[a]	-16,2568[a]
RELREP	mean	8,0602	7,5533	9,5598	7,1286	8,0243	9,0610	8,3465	0,0359	-1,0008
	N	1.910	1.180	821	615	427	1.922	6.875	0,0266	-1,2880[c]
TADVISORTIER	mean	0,3880	0,4292	0,4720	0,5061	0,5179	0,5746	0,4687	-0,1299	-0,1866
	N	13.409	7.024	4.538	3.171	2.344	10.475	40.961	-8,4596[a]	-19,9617[a]
PASTACAR	mean	0,0000	0,0018	0,0020	-0,0011	0,0046	0,0003	0,0008	-0,0045	-0,0003
	N	733.626	440.362	301.406	224.106	154.789	685.026	2.539.315	-74,0884[a]	-4,7023[a]
PASTCOMPLETED	mean	0,0075	0,2202	0,3059	0,3452	0,4039	0,5087	0,2690	-0,3964	-0,5013
	N	733.626	440.362	301.406	224.106	154.789	685.026	2.539.315	-650,0000[a]	-850,0000[a]
PASTRESOLSPEED	mean	1,2677	24,7191	36,4304	40,9773	46,7670	60,9427	31,8847	-45,4993	-59,6750
	N	733.626	440.362	301.406	224.106	154.789	685.026	2.539.315	-390,0000[a]	-540,0000[a]

[a] p<0.01, [b] p<0.05, [c] p<0.1

Table 5: Univariate tests of the dependent, advisor, acquirer and transaction variables by the advisor type

Table 5 shows the distribution of variables over the types of the advisory choices. The last two columns show the t-tests with the t-value and the differences between the unadvised (1), non-bulge-bracket bank advised (2) and bulge-bracket bank (3) advised deals.

Panel A: Dependent and bank/advisor variables

Acquirer advisor tier		unadvised	non-bulge-bracket	bulge-bracket	All Bids	t-test	t-test
Variable		1	2	3		1 - 3 = 0	2 - 3 = 0
CAR (-1, 1) value weighted	mean	0,0091	0,0081	0,0002	0,0080	0,0089	0,0079
	N	26.829	4.453	3.973	35.255	5,9225[a]	4,2051[a]
RESOLSPEED	mean	63,5196	108,6691	120,8608	76,0591	-57,3412	-12,1916
	N	29.208	5.005	4.532	38.745	-35,0785[a]	-5,6275[a]
COMPLETED	mean	0,8846	0,9355	0,9246	0,8954	-0,0399	0,0110
	N	31.324	5.058	4.574	40.956	-8,0640[a]	2,1129[b]
ADVISORFEE	mean	---	1,5381	5,0385	3,2061	---	-3,5005
	N	0	869	791	1.660	---	-14,9058[a]
IEDA	Mean	---	0,0361	0,1104	0,0714	---	-0,0743
	N	0	5.058	4.574	9.632	---	-55,2156[a]
IEDT	Mean	---	0,0357	0,1043	0,0683	---	-0,0686
	N	0	5.058	4.574	9.632	---	-52,5694[a]
ARSD	Mean	---	0,0391	0,0652	0,0515	---	-0,0261
	N	0	5.058	4.574	9.632	---	-8,6842[a]
MS	Mean	---	2,0917	20,0094	10,6004	---	-17,9176
	N	0	5.058	4.574	9.632	---	-120,0000[a]
TADVISORTIER	Mean	0,2845	0,8588	1,2986	0,4687	-1,0141	-0,4398
	N	31.329	5.058	4.574	40.961	-100,0000[a]	-28,1223[a]
RELREP	Mean	---	2,1773	13,6995	8,3465	---	-11,5223
	N	0	3.194	3.681	6.875	---	-20,9288[a]
PASTACAR	Mean	---	0,0008	0,0009	0,0008	---	0,0000
	N	0	1.368.472	1.170.843	2.539.315	---	-0,9864
PASTCOMPLETED	Mean	---	0,2324	0,3117	0,2690	---	-0,0793
	N	0	1.368.472	1.170.843	2.539.315	---	-140,0000[a]
PASTRESOLSPEED	Mean	---	27,0318	37,5648	31,8884	---	-10,5330
	N	0	1.368.472	1.170.843	2.539.315	---	-110,0000[a]

[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Table 5 (cont.): Univariate tests of the dependent, advisor, acquirer and transaction variables by the advisor type

Table 5 shows the distribution of variables over the types of the advisory choices. The last two columns show the t-tests with the t-value and the differences between the unadvised (1), non-bulge-bracket bank advised (2) and bulge-bracket bank (3) advised deals.

Panel B: Acquirer variables

Acquirer advisor tier Variable		unadvised 1	non-bulg-bracket 2	bulge-bracket 3	All Bids	t-test 1 - 3 = 0	t-test 2 - 3 = 0
DEALS3YEARS	Mean	1,7453	1,1870	1,6659	1,6675	0,0793	-0,4789
	N	31.329	5.058	4.574	40.961	1,5503[c]	-9,9511[a]
TobinsQ	Mean	1,9923	1,9990	1,9619	1,9898	0,0304	0,0371
	N	31.329	5.058	4.574	40.961	0,8520	0,8549
ITobinsQ	Mean	0,0052	0,0047	0,0054	0,0052	-0,0002	-0,0007
	N	31.329	5.058	4.574	40.961	-0,6909	-2,1494[b]
FCF	Mean	0,0096	0,0275	0,0498	0,0163	-0,0402	-0,0223
	N	31.329	5.058	4.574	40.961	-13,0545[a]	-7,6089[a]
ROA	Mean	-0,0183	-0,0039	0,0237	-0,0119	-0,0421	-0,0276
	N	31.329	5.058	4.574	40.961	-11,7241[a]	-8,2007[a]
IROA	Mean	-0,0010	-0,0009	-0,0011	-0,0010	0,0001	0,0002
	N	31.329	5.058	4.574	40.961	2,3732[a]	3,1745[a]
LEVERAGE	Mean	0,2704	0,2240	0,2664	0,2642	0,0039	-0,0424
	N	31.329	5.058	4.574	40.961	0,9381	-8,8104[a]
ILEVERAGE	Mean	0,0008	0,0007	0,0007	0,0007	0,0000	0,0000
	N	31.329	5.058	4.574	40.961	0,3867	0,1957
IS	Mean	1085	1227	1001	1093	84	226
	N	31.329	5.058	4.574	40.961	6,2378[a]	12,9078[a]

[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Table 6: Selection regressions of advised deals

Table 6 includes the first selection regressions whether the bid or acquisition is advised according to Poirier (1980). This probit regression is comparable to Servaes & Zenner (1996) that the transaction and contracting costs and information asymmetry determine the decision whether to employ a bank as M&A advisor. The dependent variable is the dummy "ADVISED" which is 1 if the acquisition is advised by at least one investment bank. To mitigate potential heteroscedasticity caused by the relation between bids/acquisition by the same acquirer the standard errors are corrected by clustering on the acquirer level (Williams (2000), Froot (1989)). The reported coefficients are the marginal effects at the mean. Year and Fama & French industry (Fama & French (1997)) fixed-effects are included but not reported. The transaction variables are omitted for brevity and included in the extended tables in the online appendix.

Dependent Variable	ADVISED		
	(1)	(2)	(3)
Independent variables	full sample	FIRST	SIXTH
TADVISORTIER	0.1721[a]	0.1713[a]	0.1417[a]
	(0.004)	(0.005)	(0.007)
DEALS3YEARS	-0.0087[a]		-0.0070[a]
	(0.001)		(0.001)
FIRST	-0.0159[a]		
	(0.005)		
SIXTH	0.0011		
	(0.008)		
FCF	0.2031[a]	0.1213[a]	0.2443[a]
	(0.026)	(0.032)	(0.076)
LEVERAGE	-0.0093	-0.0221[c]	0.0483[b]
	(0.010)	(0.013)	(0.024)
TobinsQ	0.0116[a]	0.0123[a]	0.0009
	(0.001)	(0.002)	(0.003)
ITobinsQ	-0.1409	-0.0128	-0.3250
	(0.181)	(0.240)	(0.417)
ROA	0.0044	0.0260	0.0482
	(0.021)	(0.028)	(0.051)
IS	0.0000[c]	0.0000[a]	0.0000
	(0.000)	(0.000)	(0.000)
Observations	40,961	13,403	10,434
Pseudo R-squared	0.2647	0.2290	0.3210

Standard errors in parentheses

[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Table 7: Selection regressions of the advisor choice

This table includes the second selection regressions according to Poirier (1980) of the particular advisor choice by the bidder. The regressions are used to calculate the second inverse mills ratios that are added to the structural regressions in tables 8 to 11. The variables are described and summarized in tables 2 and 3. The dependent variable is the dummy "AADVISOR" which is 1 if the investment bank is an advisor and 0 otherwise. The bank/advisor characteristics are modeled by the variables "IEDA", "IEDT", "ARSD", "PASTACAR", "PASTCOMPLETED" and "PASTRESOLSPEED" . For each bid/acquisition as many observations are available as investment banks as possible advisors are given in the SDC M&A database in the respective year. To mitigate potential heteroscedasticity caused by the relation between the otherwise identical bids/acquisition the standard errors are corrected by clustering on the bid/acquisition level (Williams (2000), Froot (1989)). The multivariate outliers are identified with the Mahalanobis D^2 measure (Hair et al. (1998), Bar-Hen & Daudin (1995), Mahalanobis (1936)).The reported coefficients are the marginal effects at the mean. Year and industry dummies to control for fixed-effects are included but not reported.

Dependent Variable	AADVISOR					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables	full sample	full sample	FIRST=1	FIRST=1	SIXTH=1	SIXTH=1
IEDA	0.0307[a]		0.0365[a]		0.0260[a]	
	(0.001)		(0.002)		(0.002)	
IEDT	0.0273[a]	0.0546[a]	0.0305[a]	0.0617[a]	0.0223[a]	0.0470[a]
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
ARSD	0.0498[a]	0.0535[a]			0.0280[a]	0.0307[a]
	(0.001)	(0.001)			(0.001)	(0.001)
PASTACAR	0.0022[a]	0.0023[a]			0.0038[a]	0.0038[a]
	(0.001)	(0.001)			(0.001)	(0.001)
PASTCOMPLETED	-0.0024[a]	-0.0025[a]	-0.0009[c]	-0.0008	-0.0030[a]	-0.0030[a]
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
PASTRESOLSPEED	-0.0000[a]	-0.0000[a]	0.0000	0.0000	-0.0000[b]	-0.0000[b]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,539,315	2,539,315	733,626	733,626	685,026	685,026
Pseudo R-squared	0.1920	0.1821	0.1009	0.0900	0.3034	0.2929

Standard errors in parentheses

[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Table 8: OLS Regression of the advisor choice on the returns (CAR (-1, +1))

This table includes the OLS regressions of the influence of the choice of the particular advisor on the returns of the bid/acquisition, given that the advisor has been chosen by the acquirer in the second selection equation and the acquirer decided to use an advisor in the first selection equation according to Poirier (1980). The dependent variable are the CARs from -1 to +1 days around the announcement date using the CRSP value weighted index. The selection bias is corrected by adding the two inverse mills ratios for the full sample computed from selection equations [1] and [2] (Poirier (1980)). For each bid/acquisition as many observations are given as advisors have been selected in the second selection equation. To mitigate potential heteroscedasiticity caused by the relation between the otherwise identical bids/acquisition the standard errors are corrected by clustering on the bid/acquisition level (Williams (2000), Froot (1989)). The potential heteroscedasticity caused by the sample estimation of the inverse mills ratios from the two selection equations is corrected using bootstrapping with 200 repetitions (Adkins & Hill (2004), Hill et al. (2003)). The multivariate outliers are identified with the Mahalanobis D^2 measure (Hair et al. (1998), Bar-Hen & Daudin (1995), Mahalanobis (1936)). Year and Fama & French (1997) industry fixed-effects are included but not reported. The transaction variables are omitted for brevity and included in the extended tables in the online appendix.

Dependent Variable	CAR (-1, 1) value weighted				
	(1)	(2)	(3)	(4)	(5)
Independent variables	full sample	full sample	full sample	full sample	full sample
IEDA	0.0092				
	(0.026)				
IEDT	0.0394	0.0453^{b}	0.0141	0.0530^{b}	0.0659^{a}
	(0.025)	(0.020)	(0.015)	(0.022)	(0.020)
ARSD	-0.0002	-0.0009	-0.0116^{c}	0.0003	0.0052
	(0.011)	(0.012)	(0.006)	(0.012)	(0.010)
FIRST	0.0006	0.0006	0.0023	-0.0025	-0.0011
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
SIXTH	-0.0078^{a}	-0.0078^{a}	-0.0082^{a}	-0.0037	-0.0025
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
DEALS3YEARS				-0.0009^{c}	-0.0010^{b}
				(0.000)	(0.000)
TADVISORTIER					-0.0006
					(0.004)
MS					-0.0003^{a}
					(0.000)
RELREP				0.0000	
				(0.000)	
IS				-0.0000	-0.0000^{c}
				(0.000)	(0.000)
ILEVERAGE				-0.7517	-1.2193^{b}
				(0.625)	(0.517)
ITobinsQ				0.2449^{b}	0.2420^{a}
				(0.107)	(0.093)
IROA				1.0159^{b}	0.6614^{c}
				(0.502)	(0.397)
inverse mills ratio [1]	0.0141^{a}	0.0141^{a}		0.0074	0.0096
	(0.002)	(0.002)		(0.005)	(0.007)
inverse mills ratio [2]	0.0046^{c}	0.0042^{c}		0.0026	0.0039^{c}
	(0.002)	(0.003)		(0.003)	(0.002)
Constant	-0.1299^{c}	-0.1290	-0.1094	0.1063	-0.1006
	(0.079)	(0.080)	(0.083)	(0.101)	(0.086)
Observations	9,532	9,532	9,532	6,958	9,532
R-squared	0.0421	0.0420	0.0357	0.0954	0.0653

Standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table 9: OLS Regression of the advisor choice on the resolution speed

This table includes the OLS regressions of the influence of the choice of the particular advisor on the resolution speed of the bid/acquisition, given that the advisor has been chosen by the acquirer in the second selection equation and the acquirer decided to use an advisor in the first selection equation according to Poirier (1980). The dependent variable is the resolution speed in days from the announcement date until the withdrawal or completion date. The selection bias is corrected by adding the two inverse mills ratios for the full sample computed from selection equations [1] and [2] (Poirier (1980)). For each bid/acquisition as many observations are given as advisors have been selected in the second selection equation. To mitigate potential heteroscedasiticity caused by the relation between the otherwise identical bids/acquisition the standard errors are corrected by clustering on the bid/acquisition level (Williams (2000), Froot (1989)). The potential heteroscedasticity caused by the sample estimation of the inverse mills ratios from the two selection equations is corrected using bootstrapping with 200 repetitions (Adkins & Hill (2004), Hill et al. (2003)). The multivariate outliers are identified with the Mahalanobis D^2 measure (Hair et al. (1998), Bar-Hen & Daudin (1995), Mahalanobis (1936)). Year and Fama & French (1997) industry fixed-effects are included but not reported. The transaction variables are omitted for brevity and included in the extended tables in the online appendix.

Dependent Variable	RESOLSPEED				
	(1)	(2)	(3)	(4)	(5)
Independent variables	full sample	full sample	full sample	full sample	full sample
IEDA	20.2948				
	(25.289)				
IEDT	38.7595	55.0172^{b}	67.1776^{a}	47.9992^{b}	61.8174^{b}
	(27.462)	(21.838)	(17.170)	(23.930)	(24.175)
ARSD	4.9033	5.5054	-21.7197^{a}	8.8517	6.5027
	(12.352)	(12.189)	(6.740)	(12.129)	(14.261)
FIRST	-0.6114	-0.6242	-5.4315^{b}	-0.1073	-1.6972
	(2.770)	(2.734)	(2.715)	(2.606)	(3.292)
SIXTH	1.6119	1.6161	2.9409	1.0280	0.1164
	(2.448)	(2.593)	(2.532)	(2.924)	(3.337)
DEALS3YEARS				0.3758	0.1553
				(0.498)	(0.567)
TADVISORTIER				-7.6279^{b}	
				(3.152)	
RELREP					0.0277
					(0.055)
MS				0.1966^{b}	
				(0.097)	
IS				-0.0000	-0.0000^{c}
				(0.000)	(0.000)
ILEVERAGE				-0.7517	-1.2193^{b}
				(0.625)	(0.517)
ITobinsQ				0.2449^{b}	0.2420^{a}
				(0.107)	(0.093)
IROA				1.0159^{b}	0.6614^{c}
				(0.502)	(0.397)
inverse mills ratio [1]	0.0141^{a}	0.0141^{a}		0.0074	0.0096
	(0.002)	(0.002)		(0.005)	(0.007)
inverse mills ratio [2]	0.0046^{c}	0.0042^{c}		0.0026	0.0039^{c}
	(0.002)	(0.003)		(0.003)	(0.002)
Constant	-0.1299^{c}	-0.1290	-0.1094	0.1063	-0.1006
	(0.079)	(0.080)	(0.083)	(0.101)	(0.086)
Observations	9,532	9,532	9,532	6,958	9,532
R-squared	0.0421	0.0420	0.0357	0.0954	0.0653

Standard errors in parentheses

[a] p<0.01, [b] p<0.05, [c] p<0.1

Table 10: OLS Regression of the advisor choice on the completion probability

This table includes the OLS regressions of the influence of the choice of the particular advisor on the completion probability of the bid/acquisition, given that the advisor has been chosen by the acquirer in the second selection equation and the acquirer decided to use an advisor in the first selection equation according to Poirier (1980). The dependent variable is the dummy "COMPLETED" that is 1 when the M&A has been completed and 0 otherwise. The selection bias is corrected by adding the two inverse mills ratios for the full sample computed from selection equations [1] and [2] (Poirier (1980)). For each bid/acquisition as many observations are given as advisors have been selected in the second selection equation. To mitigate potential heteroscedasiticity caused by the relation between the otherwise identical bids/acquisition the standard errors are corrected by clustering on the bid/acquisition level (Williams (2000), Froot (1989)). The potential heteroscedasticity caused by the sample estimation of the inverse mills ratios from the two selection equations is corrected using bootstrapping with 200 repetitions (Adkins & Hill (2004), Hill et al. (2003)). The multivariate outliers are identified with the Mahalanobis D^2 measure (Hair et al. (1998), Bar-Hen & Daudin (1995), Mahalanobis (1936)). Year and Fama & French (1997) industry fixed-effects are included but not reported. The transaction variables are omitted for brevity and included in the extended tables in the online appendix.

Dependent Variable	COMPLETED				
	(1)	(2)	(3)	(4)	(5)
Independent variables	full sample	full sample	full sample	full sample	full sample
IEDA	0.0031				
	(0.087)				
IEDT	0.0002	-0.0092	-0.0367	-0.0183	-0.0183
	(0.089)	(0.053)	(0.043)	(0.066)	(0.066)
ARSD	0.0359	0.0278	0.0436[b]	0.0680[b]	0.0680[b]
	(0.030)	(0.030)	(0.019)	(0.033)	(0.032)
FIRST	-0.0032	-0.0032	0.0016	-0.0060	-0.0060
	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
SIXTH	-0.0034	-0.0034	-0.0046	0.0123	0.0123
	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
DEALS3YEARS				-0.0023	-0.0023
				(0.002)	(0.002)
TADVISORTIER				-0.0134	-0.0134
				(0.012)	(0.012)
RELREP				0.0002[c]	0.0002[c]
				(0.000)	(0.000)
MS				0.0003	0.0003
				(0.000)	(0.000)
ILEVERAGE				-2.4046	-2.4046
				(2.090)	(2.093)
ITobinsQ				-0.4272	-0.4272
				(0.401)	(0.433)
IROA				-0.8039	-0.8039
				(1.542)	(1.785)
inverse mills ratio [1]	0.0461[a]	0.0460[a]		-0.0536[b]	-0.0536[b]
	(0.006)	(0.006)		(0.023)	(0.021)
inverse mills ratio [2]	0.0015	-0.0010		0.0051	0.0051
	(0.006)	(0.007)		(0.007)	(0.007)
Constant	0.5749[a]	0.5808[a]	0.6054[a]	1.1479[a]	1.1479[a]
	(0.189)	(0.198)	(0.189)	(0.201)	(0.203)
Observations	10,929	10,929	10,929	7,990	7,990
R-squared	0.0330	0.0330	0.0254	0.1940	0.1940

Standard errors in parentheses

[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Table 11: OLS Regression of the advisor choice on the advisor fees

This table includes the OLS regressions of the influence of the choice of the particular advisor on the acquirer advisor fees of the bid/acquisition, given that the advisor has been chosen by the acquirer in the second selection equation and the acquirer decided to use an advisor in the first selection equation according to Poirier (1980). The dependent variable are the acquirer advisor fees. The selection bias is corrected by adding the two inverse mills ratios for the full sample computed from selection equations [1] and [2] (Poirier (1980)). For each bid/acquisition as many observations are given as advisors have been selected in the second selection equation. To mitigate potential heteroscedasiticity caused by the relation between the otherwise identical bids/acquisition the standard errors are corrected by clustering on the bid/acquisition level (Williams (2000), Froot (1989)). The potential heteroscedasticity caused by the sample estimation of the inverse mills ratios from the two selection equations is corrected using bootstrapping with 200 repetitions (Adkins & Hill (2004), Hill et al. (2003)). The multivariate outliers are identified with the Mahalanobis D² measure (Hair et al. (1998), Bar-Hen & Daudin (1995), Mahalanobis (1936)). Year and Fama & French (1997) industry fixed-effects are included but not reported. The transaction variables are omitted for brevity and included in the extended tables in the online appendix.

Dependent Variable	ADVISORFEE			
	(1)	(2)	(3)	(4)
Independent variables	full sample	full sample	full sample	full sample
IEDA	1.1302			
	(3.628)			
IEDT	8.2352[c]	9.5689[a]	11.1758[a]	-1.9131
	(4.259)	(2.952)	(2.521)	(2.716)
ARSD	3.7278[b]	4.0684[b]	3.0302[c]	5.6692[a]
	(1.899)	(2.016)	(1.609)	(1.800)
FIRST	-0.2211	-0.2266	-0.4109	-0.3325
	(0.343)	(0.322)	(0.348)	(0.336)
SIXTH	1.6430[a]	1.6401[a]	1.8992[a]	0.9489[b]
	(0.473)	(0.499)	(0.492)	(0.473)
DEALS3YEARS				0.0210
				(0.083)
TADVISORTIER				0.2242
				(0.705)
RELREP				-0.0344[a]
				(0.009)
MS				0.1825[a]
				(0.029)
ILEVERAGE				-1.7991
				(60.416)
ITobinsQ				-16.9678
				(21.023)
IROA				-112.9833
				(130.785)
inverse mills ratio [1]	-4.6472[a]	-4.6368[a]		-3.2322[a]
	(0.349)	(0.336)		(0.893)
inverse mills ratio [2]	0.1286	0.2225		0.4312
	(0.293)	(0.319)		(0.299)
Constant	2.1945	1.9418	0.9989	1.8921
	(3.296)	(2.721)	(3.204)	(3.856)
Observations	1,955	1,955	1,955	1,823
R-squared	0.2962	0.2965	0.2174	0.4497

Standard errors in parentheses

[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Table 12: First Stage Ordered Probit Regressions of the Choice of the Advisor Type (0/1/2)

Table 12 reports the first stage ordered probit regressions of the choice of the advisor given the advisor, transaction and acquirer characteristics. The dependent variable is ADVISORCHOICE. The standard errors are clustered on the bid/acquisition level, because for each bid/acquisition there are as many observaitons as advisors are chosen, with at least one in the case of an unadvised bid/acquisition (Williams (2000), Froot (1989)). The ordered probit regressions are run on the full sample, reporting the marginal effects at the mean for each possible outcome of the ordered dependent variable ADVISORCHOICE. Year and Fama & French (1997) industry dummies are include but not reported. The transaction variables are omitted for brevity and included in the extended tables in the online appendix.

Dependent Variable	ADVISORCHOICE					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables	Outcome(1)	Outcome(2)	Outcome(3)	Outcome(1)	Outcome(2)	Outcome(3)
IEDA	-2.8946[a]	2.8726[a]	0.0220[a]			
	(0.274)	(0.272)	(0.004)			
IEDT	-2.6114[a]	2.5916[a]	0.0198[a]	-4.8825[a]	4.8377[a]	0.0447[a]
	(0.240)	(0.238)	(0.003)	(0.215)	(0.218)	(0.007)
ARSD	-0.6347[a]	0.6298[a]	0.0048[a]	-0.7156[a]	0.7090[a]	0.0066[a]
	(0.100)	(0.099)	(0.001)	(0.097)	(0.096)	(0.002)
TADVISORTIER	-0.1380[a]	0.1369[a]	0.0010[a]	-0.1383[a]	0.1370[a]	0.0013[a]
	(0.008)	(0.008)	(0.000)	(0.007)	(0.007)	(0.000)
MS	-0.1294[a]	0.1284[a]	0.0010[a]	-0.1308[a]	0.1296[a]	0.0012[a]
	(0.004)	(0.004)	(0.000)	(0.006)	(0.006)	(0.000)
DEALS3YEARS	0.0063[b]	-0.0063[b]	-0.0000[b]	0.0065[b]	-0.0064[b]	-0.0001[b]
	(0.003)	(0.003)	(0.000)	(0.003)	(0.003)	(0.000)
FIRST	-0.0122	0.0121	0.0001	-0.0115	0.0114	0.0001
	(0.010)	(0.010)	(0.000)	(0.011)	(0.011)	(0.000)
SIXTH	0.0687[a]	-0.0683[a]	-0.0005[a]	0.0688[a]	-0.0683[a]	-0.0006[a]
	(0.014)	(0.013)	(0.000)	(0.014)	(0.014)	(0.000)
FCF	-0.2142[a]	0.2126[a]	0.0016[a]	-0.2184[a]	0.2164[a]	0.0020[a]
	(0.042)	(0.042)	(0.000)	(0.033)	(0.032)	(0.000)
LEVERAGE	0.0684[a]	-0.0679[a]	-0.0005[a]	0.0666[a]	-0.0659[a]	-0.0006[a]
	(0.012)	(0.012)	(0.000)	(0.015)	(0.015)	(0.000)
TobinsQ	-0.0132[a]	0.0131[a]	0.0001[a]	-0.0134[a]	0.0133[a]	0.0001[a]
	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)	(0.000)
ITobinsQ	-0.4632	0.4597	0.0035*	-0.4496	0.4455	0.0041
	(0.296)	(0.294)	(0.002)	(0.324)	(0.320)	(0.003)
ROA	0.0183	-0.0182	-0.0001	0.0203	-0.0201	-0.0002
	(0.032)	(0.032)	(0.000)	(0.021)	(0.021)	(0.000)
IS	-0.0000[a]	0.0000[a]	0.0000[a]	-0.0000[a]	0.0000[a]	0.0000[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	42,258	42,258	42,258	42,258	42,258	42,258
Pseudo R-squared	0.6466	0.6466	0.6466	0.6431	0.6431	0.6431

Standard errors in parentheses

[a] p<0.01, [b] p<0.05, [c] p<0.1

Table 13: Second Stage Ordered Probit Regressions of the returns (CAR(-1, 1))

Table 13 reports the second stage ordered probit regressions of the choice of the advisor given the advisor, transaction and acquirer characteristics. The dependent variable is CAR (-1, 1) value weighted. The standard errors are clustered on the bid/acquisition level, because for each bid/acquisition there are as many observatons as advisors are chosen, with at least one in the case of an unadvised bid/acquisition (Williams (2000), Froot (1989)). The ordered probit regressions are run on the full sample, reporting the marginal effects at the mean for each possible outcome of the first stage dependent variable ADVISORCHOICE. Year and Fama & French (1997) industry dummies are include but not reported. The transaction variables are omitted for brevity and included in the extended tables in the online appendix.

Dependent Variable	CAR (-1, 1) value weighted					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables	Outcome(1)	Outcome(2)	Outcome(3)	Outcome(1)	Outcome(2)	Outcome(3)
IEDA	0.0000	0.1117	0.0059			
	(0.000)	(0.079)	(0.029)			
IEDT	0.0000	0.0499	0.0603[b]	0.0000	0.1526	0.0643[a]
	(0.000)	(0.073)	(0.026)	(0.000)	(0.112)	(0.022)
ARSD	0.0000	-0.0008	-0.0009	0.0000	0.0039	-0.0007
	(0.000)	(0.017)	(0.008)	(0.000)	(0.018)	(0.008)
DEALS3YEARS	-0.0000	0.0000	-0.0009[b]	0.0000	0.0000	-0.0009[c]
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
TADVISORTIER	-0.0031[b]	-0.0036	-0.0019	-0.0031[b]	-0.0032	-0.0019
	(0.002)	(0.004)	(0.002)	(0.002)	(0.005)	(0.002)
MS	0.0000	0.0026	0.0000	0.0000	0.0030	0.0000
	(0.000)	(0.003)	(0.000)	(0.000)	(0.003)	(0.000)
FIRST	0.0004	-0.0002	-0.0000	0.0004	-0.0003	-0.0000
	(0.001)	(0.004)	(0.003)	(0.001)	(0.004)	(0.003)
SIXTH	-0.0022[c]	-0.0060	-0.0027	-0.0022[c]	-0.0062[c]	-0.0028
	(0.001)	(0.004)	(0.003)	(0.001)	(0.003)	(0.004)
IS	-0.0000[b]	-0.0000[b]	-0.0000	-0.0000[c]	-0.0000[b]	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ILEVERAGE	0.0337	-1.0754[b]	-1.1231	0.0337	-1.0975[c]	-1.1211
	(0.234)	(0.521)	(0.717)	(0.178)	(0.633)	(0.796)
ITobinsQ	0.1081[a]	0.0923	0.3325[a]	0.1082[c]	0.0924	0.3347[a]
	(0.042)	(0.129)	(0.124)	(0.057)	(0.169)	(0.111)
IROA	0.4122[b]	0.3266	1.0546[b]	0.4125[c]	0.3176	1.0622[b]
	(0.169)	(0.633)	(0.493)	(0.234)	(0.776)	(0.487)
inverse mills ratio	-0.0131	0.0145	-0.0018	-0.0133	0.0160	-0.0017
	(0.015)	(0.013)	(0.004)	(0.015)	(0.015)	(0.003)
Constant	0.0219	-0.0020	-0.0539	0.0223	-0.0060	-0.0541
	(0.021)	(0.109)	(0.074)	(0.022)	(0.106)	(0.083)
Observations	26,829	4,743	4,789	26,829	4,743	4,789
R-squared	0.0184	0.0499	0.1425	0.0184	0.0498	0.1425

Standard errors in parentheses

[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Table 14: Tests of the differences in realized and hypothetical returns by the advisor type

The univariate t-test is used to test whether the differences in the predicted returns between the unadvised, non-bulge-bracket bank and the bulge-bracket bank advised deals are significant. The last two columns show the t-tests with the mean difference between the unadvised deals (1) or non-bulge-bracket advisor advised deals (2) and the deals advised by a bulge-bracket bank (3) on the side of the acquirer. The sample used are the 40,961 deals/bids multiplied with the SDC Top-50 banks as possible advisors and the alternative not to use an advisor . The returns are predicted using the regression equations from table 10 with the industry experience by deals in the target industry. The inverse mills ratios from the first stage ordered probit regressions in table 9 are used as well. For each bid and possible advisor matching and the unadvised alternative the returns are predicted.

Panel A: Comparison of realized and hypothetical returns for bulge-bracket bank advised deals (N=2,059)

Acquirer advisor tier Variable		bulge-bracket real return	non-bulge-bracket hypothetical return	unadvised hypothetical return
CAR (-1, 1) value weighted	Mean	-0.0180[a]	-0.0469[a]	-0.1381[a]
Improvement	Mean	0.0000	-0.0290[a]	-0.1201[a]

Panel B: Comparison of realized and hypothetical returns for non-bulge-bracket bank advised deals (N=1,638)

Acquirer advisor tier Variable		bulge-bracket hypothetical return	non-bulge-bracket real return	unadvised hypothetical return
CAR (-1, 1) value weighted	Mean	-0.0100[a]	-0.0167[a]	-0.0197[a]
Improvement	Mean	0.0067[a]	0.0000	-0.0030

Panel C: Comparison of realized and hypothetical returns for unadvised deals (N=3,483)

Acquirer advisor tier Variable		bulge-bracket hypothetical return	non-bulge-bracket hypothetical return	unadvised real return
CAR (-1, 1) value weighted	Mean	0.0106[a]	-0.0553[a]	0.0009
Improvement	Mean	0.0097[a]	-0.0562[a]	0.0000

[a] p<0.01, [b] p<0.05, [c] p<0.1