Comparative Advantage, Industry Specialization, and the Role of Investment Banks in M&As

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ABSTRACT

This paper examines the role of industry specialist advisors in M&A transactions using the Additive Revealed Comparative Advantage (ARCA) index to proxy advisors' relative level of industry specialization prior to deal announcement. We find that industry specialist advisors are able to generate higher returns for their acquirer clients, especially in cross-industry transactions, with the value creation resulting primarily from the selection of more synergistic targets and negotiating to pay a lower takeover premium. While specialist advisors are associated with a lower completion probability, they are able to complete tender offers in less time. In addition to superior advice, we find that specialist advisor charge lower fees, suggesting that they are able to pass some cost efficiencies onto their bidder clients. The findings are consistent with the traditional perception of the superiority of industry specialists and show that specialization is beneficial to the M&A advisory market.

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Keywords: Industry Specialist advisors; Acquirers, Abnormal Returns, Advisory Fees, Deal Completion

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1. Introduction

This paper examines the effect of industry specialist advisors on M&A outcomes for acquirer clients. The idea that specialization enables productivity gains is well established. Differentiation by industry enables the specialist to gain competitive advantage and to compete on dimensions other than price. Indeed, existing research suggests that industry specialization fosters the development of core competencies, and this effect is empirically documented in diverse fields such as auditing (Craswell, Francis and Taylor (1995); Balsam, Krishnan and Yang (2003); andDunn and Mayhew (2004)), security analysis (Clement (1999); Jacob, Lys and Neale (1999)), and private equity (Cressy, Munari and Malipiero (2007)). In the context of M&As, anecdotal evidence suggests that even large investment banks, which typically have diversified business across industries, often maintain groups specializing along industry lines. Consistent with this observation, our data indicate that investment banks do specialize and the use of industry specialists tends to dominate in the M&A market. For example, during the period between 1985 and 2010, 55% (52%) of acquirers (targets) hired an industry specialist to advise on a transaction. Despite specialists being frequently used in M&A transactions, there is little research that examines whether industry specialization by advisors benefits acquiring firms. With the exception of Song, Wei and Zhou (2013) who explore the value of "boutique advisors", most research into the role of investment banks has been limited to the significance of advisor reputation in the M&A advisory market (e.g., McLaughlin (1992); Servaes and Zenner (1996); Rau (2000); Golubov, Petmezas and Travlos (2012); Walter, Yawson and Yeung (2008); Sibilkov and McConnell (2014)).

In this paper, we shift away from advisor reputation in the M&A market to consider the value-added role of industry specialist advisors on two important fronts. First, we examine how industry specialization of bidder advisors affects acquisition outcomes, measured by bidder abnormal returns, deal premium, synergy, completion probability, and deal duration. Drawing on the established theories of industry specialization and organizational learning (see e.g., Dierickx and Cool (1989)), we hypothesize that industry specialization enables advisors to concentrate both resources and learning effort on a narrow range of industries, which accelerates the acquisition of industry-specific knowledge and skill. As experience accumulates over time, industry specialist advisors are likely to gain a competitive advantage doing deals specific to their domain. For instance they may have developed more sophisticated valuation models which can help acquiring firm better understand the target and the resulting synergies, given the industry trend and prospects. . By working on deals and interacting closely with firms specific to an industry, specialist advisors may also be able to establish more extensive networks, from which useful information can be extracted to maximize acquiring firms' value. . We thus expect that industry specialization is associated with better acquisition outcomes, *ceteris paribus*. Second, industry specialization affects M&A advisory fees. The theoretical models of Klein and Leffler (1981) and Chemmanur and Fulghieri (1994) posit that firms offering high quality services will receive premium fees to reflect the increased costs of producing the superior service. Accordingly, if industry specialist advisors are able to offer superior service, they should be associated with higher advisory fees. On the other hand, industry specialization may generate cost efficiencies through economies of scale and scope. This may enable industry specialist advisors to compete for deals by charging lower fees (Mayhew and Wilkins (2003); Carson (2009)). Given these conflicting predictions, assessing the effects of industry specialization on the level of M&A advisory fees becomes an empirical issue.

We use the Additive Revealed Comparative Advantage (ARCA) index, adapted from the international trade and technological specialization literature, to determine advisors' respective specialization levels (see Balassa (1965); Archibugi and Pianta (1994); Cressy, et al. (2007)). This measure captures the comparative advantage of an investment bank in an industry, and allows specialization levels to be comparable across investment banks and across industries.

Using a large sample of M&A transactions announced in the U.S. over the period between 1985 and 2010, we find that advisor industry specialization has a positive and significant effect on bidder abnormal returns after taking into account selection bias. The effect is more pronounced in cross than related-industry transactions, and primarily comes from the deals advised by advisors who has specialized in the bidder's as opposed to the target's industry. In terms of the sources through which specialist advisors add value to acquirers, we find that it primarily stems from specialist advisors' ability to both reduce takeover premiums and locate more profitable targets for their acquirer clients. Overall, the evidence is consistent with the prediction that industry specialization allows advisors to build competitive advantage in advising deals specific to their specialized domain. Further, we find evidence that advisor industry specialization is associated with lower probability of completing a deal, and longer (shorter) time to completion in merger (tender) offers. Lastly, our analysis on the pricing of M&A advisory service reveals that advisor industry specialization has a significant and negative impact on advisory fees. This evidence is most consistent with the proposition that industry specialization allows some cost efficiencies to be passed onto bidder clients.

This paper contributes to the M&A literature in several ways. It is the first study, to our knowledge, that examines the value-added role of industry specialists in M&As. By using the ARCA index as a proxy for industry specialization, we show that industry specialist advisors significantly enhance the shareholder value of acquiring firms by reducing the cost of acquisition and locating more synergistic targets. The study also provides new insights into the determinants of M&A advisory fees. We show that advisor industry specialization is an important factor affecting advisory fees. By reducing costs through economies of scale, industry specialization enables advisors to charge lower fees. Finally, the study offers practical solutions for the choice of financial advisors in M&A transactions. For instance, given that investment banks commonly advertise their specialized industries online, our findings help bidding firms make rational and more informed choices of financial advisors.

The remainder of the paper is organized as follows. Section 2 presents the theory and Section 3 outlines the data and sample construction procedures. This is followed by the empirical results in Section 4. Section 5 concludes the paper.

2. Theory

2.1. Industry Specialization and M&A Advisors

Industry specialization is commonly defined as the degree to which a firm concentrates on a single or group of related industries in which it has a comparative advantage (Argote (1999); Jacobides and Winter (2005); Hartfield, Liebeskind and Opler (1996); Chamberlin (1933), Friedman (1953), Lado, Boyd and Wright (1992)). The notion that industry specialization improves performance has long been recognized (Ethier (1982); Romer (1987)). Two hypotheses relating to the resulting improved performance from specialization have been put forward in the literature. First, industry specialization facilitates the development of specialized factors of production that are necessary for firms to compete at low cost and/or produce high quality products in their focal industries (Montgomery and Wernerfelt (1988); Hartfield, et al. (1996); Solomon, Shields and Whittington (1999); Jacob, et al. (1999); Moroney and Simnett (2009); Carson (2009)). Second, industry specialization leads to more effective learning, thus accelerating the acquisition of industry-specific knowledge and skills that are important to attaining superior performance (Bonner and Lewis (1990); Schilling, Vidal, Ployhart and Marangono (2003)). For instance, as experience accumulates, specialized firms' knowledge of focal industries, such as the prevailing norms, regulation, technologies and competitors, will be deepened. This allows specialized firms to gain a competitive advantage in executing the tasks in their specialized domain (Jacobides and Winter (2005)).

Drawing on the above-mentioned theories, we expect industry specialist advisors to generate better acquisition outcomes in their specialized industry relative to their non-specialized counterparts. Specialist advisors, for instance, may have better understanding of a bidder client's needs which permits them to customize the deal to meet the acquirer's specific strategic plan.They may also have superior knowledge about the profitability of potential targets and the associated sources of synergies (or value destruction) in their specialized industries (Makadok and Barney (2001); Carson (2009)). This may permit them to identify target whose value drivers are better aligned with the acquirer. In addition, while M&A deals from the same industry parallel each other in certain fundamental ways (Haleblian and Finkelstein (1999); Makadok and Barney (2001)), they are heterogeneous in that they are client-specific (Hayward (2002)). This feature makes it particularly important for advisors to properly distinguish between deals even if they are from the same industry, since prior experience may not be relevant and directly applicable to the present deal (Mukherjee, Lapre and Wassenhove (1998)). Specialization minimizes the risks of drawing incorrect infrerence from experience by creating a learning environment, in which advisors are able to constantly explore a diverse range of deals from the same industry and adaptively learn the underlying differences and connections between previous deals and the current deal. By accumulating insights into what works and what does not for deals in a specific industry, specialist advisors should be more effective in utilizing their prior experience to properly advise deals from their specialized domain (Hayward (2002); Schilling, et al. (2003)). This line of reasoning leads us to expect that industry specialist advisors will be associated with better M&A outcomes.

It is possible to argue that compared to industrial firms such as manufacturers, investment banks have more limited specialized factors of production because difference in advisory skill sets across industries is not clear cut. Nevertheless anecdotal evidence shows that investment banks create industry groups, a practice that amounts to a specialized factor of production. Even though a large component of advisory skills is likely general and transferable across industries, the validity of the industry-specific, non-transferable part of the skill set cannot be disregarded. Industry-level factors (e.g., industry profitability and prospects) can significantly affect the choice of targets. Selecting an appropriate target, for example, requires an advisor to have accurate and updated knowledge of the general trend of the market as well as how industries of the target and the acquirer will perform under different economic conditions. Moreover, industry-level factors play a role in the selection of valuation techniques to price a firm's assets. For example, the methodology used to evaluate a high-tech firm that has a large proportion of intangible assets will be clearly different from that used to value a manufacturing firm with a large proportion of tangible assets. Specializing along industry lines should help investment banks perform better in providing such valuation advisory services.

Advisor industry specialization has important implications for M&A advisory fees as well. For example, Klein and Leffler (1981) model the relationship between quality and price premium in a product market, where firms need to repeatedly sell their products to clients and the quality of the products can only be known after the purchase (i.e., not ex-ante observable). In this setting, a price premium arises in order to compensate firms for the increased costs incurred in producing quality. It also serves as an incentive to firms to continually supply high quality products. This model can be extended to the M&A advisory market in the sense that investment banks also need to repeatedly sell a service whose quality is not observable *ex-ante* (Kale, Kini and Ryan (2003)). In addition, Chemmanur and Fulghieri (1994) model the relationship between quality, reputation, and fees specific to the investment banking industry and conclude that investment banks offering higher quality service charge higher fees. Consequently, if industry specialization produces high quality service, it would have a favorable impact on the advisory fees received by specialist advisors.

Conversely, industry specialization can generate cost efficiencies, which may allow specialist advisors to compete for deals through passing cost savings onto their bidder clients (Mayhew and Wilkins (2003)). Cost efficiencies can come from economies of knowledge sharing. As an example, while developing industry-specialized factors of production is costly, the costs can nevertheless be spread over a relatively large client base (Mayhew and Wilkins (2003)). This leads to an expectation that industry specialists will have lower M&A advisory fees.

2.2. Measuring Industry Specialization

A standard measure of specialization is the index of Revealed Comparative Advantage (RCA). The RCA has been widely used in the international trade and technological specialization literature (Balassa (1965) Balassa, 1965; Archibugi and Pianta (1994)), and also in the field of corporate finance (e.g., Cressy, et al. (2007)). The RCA index has a basic assumption that firms specialize in the industries in which they have a comparative advantage (Chamberlin (1933); Friedman (1953)). The specialization choice and the resulting inter-firm differences in capital cost, factors of production, and quality should, therefore, be "revealed" through the real-world inter-firm performance across industries (Balassa (1965)). In the M&A sector, the RCA index can be written as: $RCA_j^i = \left(X_j^i / X^i\right) / \left(X_j^A / X^A\right)$ (1)

Where: RCA_j^i=the RCA value of $investment\ bank_i$ in $industry_j$; X_j^i=the value of M&A deals advised by $investment\ bank_i$ in in $industry_j$; X^i = the value of M&A deals advised by $investment\ bank_i$ across all the industries; X_j^A=the total value of M&A deals advised in $industry_j$ by $all\ investment\ banks$;; X^A=the total value of M&A deals advised by $all\ investment\ banks$ across all the industries.

By factoring in industry and bank sizes, the RCA index ensures industry specialization levels to be comparable across banks and industries. In particular, this measure compares the portfolio share of $industry_j$ in $investment\ bank_i$ $\left(X_j^i/X^i\right)$ to the expected portfolio share of the same industry for an average investment bank $\left(X_j^A/X^A\right)$. If the RCA value is greater than one, $investment\ bank_i$ is specialized in $industry_j$ relative to the reference banks. In a numerical example, consider an investment bank$_i$, which advised M&A deals with a total value of \$10 million across all industries(X^i), of which \$2 million came from the high-tech industry (X_j^i). The bank's portfolio share of the high-tech industry is, therefore, 20%. Now suppose the aggregate value of M&A deals was \$1 billion in the high-tech industry (X_j^A) and \$10 billion across all industries (X^A). In an average investment bank's portfolio, the share of high-tech industry will be 10%. Obviously, bank$_i$ is relatively specialized in the high-tech industry when compared to the average investment bank. Consistent with this intuition, the RCA value of bank$_i$ equals two, suggesting that it is a specialist in the high-tech industry).

A potential problem of the RCA index is that it can have an unstable mean which is greater than the theoretical value of zero, and an asymmetric distribution which is sensitive to the classifications of industries (Hoen and Oostaerhaven (2006)). These statistical properties make the economic interpretation of RCA values potentially problematic. Consequently, we employ a variation of the RCA index, namely, the Additive RCA, which addresses the aforementionedproblems (Hoen and Oostaerhaven (2006)). Formally, the ARCA index can be written as:

$$ARCA_j^i = (X_j^i / X^i) - (X_j^A / X^A) \tag{2}$$

where, $ARCA_j^i$ is the ARCA of investment bank$_i$ in industry$_j$. Other notations are the same as defined in equation (1). The ARCA index compares the portfolio share of $industry_j$ in $investment\ bank_i$ with the share of the same industry in an average investment bank's portfolio. It differs from the RCA measure in the sense that it takes the difference between the portfolio shares instead of the quotient as in the equation (1) above. Accordingly, if the ARCA value is greater than zero, $investment\ bank_i$ is relatively specialized in $industry_j$, compared with the reference banks. Conversely, an ARCA value less than zero is interpreted as the investment bank being less specialized in that industry relative to the average investment bank.

3. Sample and Data

3.1. Sample Construction

The data on M&A transactions are drawn from *Thomson Financials Securities Data Collection Platinum (SDC)* database. While our sample covers the period between January 1985 and December 2010, the data are collected from 1980 because the estimation of the industry specialization measure requires information for each advisor five years prior to the deal's announcement. Both successful and unsuccessful deals announced from 1980 to 2010 are included if (1) the payment method is disclosed by SDC; (2) the transaction value is greater than $1 million; and (3) there is at least one investment bank advising the acquirer (rumoured deals are excluded).[1] The initial sample contains 19,060 transactions. We exclude deals classified as bankruptcy acquisitions, liquidations, leveraged buyouts, privatizations, repurchases, restructurings, reverse takeovers and 'going private' transactions. Applying this filter

[1]We did not give consideration to whether the deal is completed or withdrawn because investment banks are expected to learn and accumulate industry-specific knowledge as long as they engage in deals announced in their focal industries.

reduces the sample to 15,848 observations. We apply a further filter to our sample to include only deals where the acquiring firm owns less than 10% of the initial stake and seeks to own more than 50% after the transaction. This reduces the sample to 13,409 transactions.[2]

We use this sample to calculate industry specialization levels of financial advisors using the ARCA methodology. We define industry using the 3-digit SIC code in order to account for the fluctuation in industry mix of M&As. We calculate individual advisors' industry specialization based on the total value of M&A deals advised by each bank over the five years prior to the announcement date. A five-year rolling window is chosen to account for the dynamics in the M&A advisory market and because industry expertise requires time to develop. Full credit is given to each advisor used by bidders or targets, regardless of the number of advisors engaged in a particular deal.

To ensure the accuracy of the industry specialization level for each advisor, we made the following adjustments. First, because SDC occasionally uses different names for the same advising bank (e.g., deals advised by 'Citi' are regarded as different from those advised by "Citigroup"), advisor names in such cases are combined into one when measuring the industry specialization levels. Second, industry-specific knowledge of different investment banks is expected to be brought together through M&As among advisors themselves. This will improve the performance of the deals advised by the newly merged banks. We therefore track all the mergers and acquisitions among investment banks across the sample period. For instance, Merrill Lynch and Banc of America Securities LLC merged to form Bank of America Merrill Lynch in 2008. Thus, if a deal advised by Merrill Lynch in an industry takes place before its merger with Banc of America Securities LLC, we account for all the deals advised by Merrill Lynch alone in that industry over five years prior to the announcement date. However, when a deal is advised by the newly merged bank, Bank of America Merrill Lynch, we take into account the deals advised by both banks in that industry during the five years preceding the announcement date. In the case where a bidding firm hires multiple advisors, we assign the highest degree of industry specialization among these advisors

[2]By definition if an investment bank advises on only one deal in the five year period, then it will automatically be classified as a specialist. Consequently, we remove all investment banks that advised only one deal.

to the deal. This treatment is consistent with prior studies such as Rau (2000).After obtaining the industry specialization level for each advisor, we exclude observations from 1980 to 1984. The final sample consists of 12,020 deals. Out of these, 8,266 deals involve a bidder that has sufficient data from CRSP database to measure abnormal returns at the announcement date, while only 1,886 deals have advisory fees disclosed by SDC. Our estimation based on the industry specialization measure, ARCA, indicates that industry specialist advisors dominate in the M&A advisory market. We find that the use of industry specialist advisors on the acquirer and the target side represented 55.45% and 52.48%, respectively.

3.2. Sample Statistics

The thrust of this paper is to examine the role of financial advisor specialization. As such, an important concern is whether the industry specialization measure employed here captures attributes of investment banks other than reputation in the M&A market, as measured by the traditional approach of the league table rankings. We, therefore, downloaded financial advisors league tables from *Thomson Financials SDC* database and ranked advisors based on the value of deals they advised. The top-tier specification is similar toGolubov, et al. (2012).[3] In untabulated correlations matrix, we find a positive and significant, though very low, correlation of the top-8 advisor dummy with the dummies of industry specialist advisor (0.0525) suggesting that top-8 advisors do not constitute a significant proportion of industry specialist advisors. This is expected because larger, and more established banks, are more likely to diversify across industries than to specialize, compared to smaller investment banks.

3.3. Univariate Analysis

[3]The following eight financial advisors are classified as the top-8 advisors: Goldman Sachs, Merrill Lynch (now Bank of America Merrill Lynch), Morgan Stanley, JP Morgan, Citi, Credit Suisse, Lehman Brothers (now Barclays Capital) and UBS.

Table 1 reports the descriptive statistics for the full sample as well as for the types of bidder advisors classified using a cut-off of a zero ARCA value. We use the standard event study methodology to compute the cumulative abnormal returns (CARs) accruing to the acquirers over the event windows (-1, +1) around the announcement date. The CARs are measured based on the market model with a benchmark of the CRSP value weighted index and parameters estimated over a period from 300 days to 91 days prior to the announcement date. The results remain essentially unchanged when we use an equally weighted market index.

The mean (median) value of the 3-day bidder CARs in the full sample are 0.3% (0%). Acquirers using industry specialist advisors are, on average, associated with lower bidder CARs compared to those that do not use industry specialists. For example, deals advised by industry specialist advisors have a mean (median) 3-day bidder CAR of 0.0% (-0.3%), while transactions advised by non-specialist advisors have a higher mean (median) CAR of 0.7% (0.2%). Acquirers that use industry specialist pay lower mean (median) percentage of premiums of 1.393% (1.929%) compare to acquirers that do not use specialist advisors at the mean and median percentage of premiums of 1.459% and 2%, respectively.

Panel A also indicates that industry specialist advisors are associated with significantly longer deal duration (105.7 days versus 87.0 days) than their non-specialized counterparts. With regard to advisory fees, the mean (median) level of fees is $4.180 ($1.50) million for acquirers using industry specialist and $3.471 ($1.45) million for advisors who do not use industry specialist. The difference between the two groups is statistically significant at the 5% level for the mean.

Panel B of Table 1 presents statistics for deal characteristics and shows that industry specialist advisors are more likely to be used if (1) the transaction is large; (2) the bid is for a public or private target; (3) the acquisition is financed by stock, and they are less likely to be hired if it is a tender offer. These observations indicate that industry specialists are more likely to be used in complex transactions. Nevertheless, we also find that compared to their non-industry specialist counterparts, industry specialist advisors are hired less frequently in cross-border and cross-industry transactions. A possible reason is that bidding firms undertaking diversifying acquisitions appreciate the diverse experience of larger investment banks more than the deep, yet narrow, knowledge base possessed by industry specialists.

In terms of bidder characteristics, panel C of Table 1 indicates that industry specialist advisors are associated with bidders that exhibit higher run-up (8.6% versus 6.9%) or lower free cash flow (4.9% versus 5.8%), when compared to bidder clients of non-acquirer-industry specialists. There are, however, no significant differences in bidder size, Tobin's Q, leverage, and sigma, between the two groups of advisors.[4]

[Insert Table 1 here]

4. Empirical Analysis

4.1. Endogeneity Control

Table 1 shows that the use of specialist advisors is associated with remarkably different acquirer and deal characteristics. This suggests that acquirer-advisor matching is unlikely to be random. In addition, the use of an industry specialist advisor is a choice on the part of the bidder. The endogenous selection process, therefore, may bias OLS estimates of the impact of industry specialist on acquisition outcomes.

More specifically, our primary regression model of interest is:

$$y_i = \gamma industryspecialsit_i + X_i\beta + \varepsilon_i, \qquad (3)$$

where y_i is the acquisition outcome measured by acquirer abnormal return, takeover premium, synergy, deal completion probability, time to complete a deal, and advisory fee. X_i is a vector of exogenous variables affecting y_i; $industryspecialsit_i$ is the variable of interest measured using the ARCA index. It is included in the model as a dummy variable indicating whether or not an acquiring firm employs an

[4]Sigma measures a bidding firms' idiosyncratic volatility and is defined as the standard deviation of the market-adjusted daily returns of the bidder's stock over a 200-day window (-205, -6) (Moeller, Schlingemann and Stulz, 2007).

industry specialist advisor; and ε_i is the error term. In this setup, the OLS estimator will yield consistent estimates of specialist advisor if the acquirer's choice of advisor is not affected by unobservable factors that are also correlated with the error term ε_i in equation (3). That is, $industryspecialsit_i$ must be exogenous.

As the matching is unlikely to be random, we use a two-stage estimator to correct for self-selection bias (e.g., Maddala (1983); Terza (1998)). In particular, we model the endogenous decision of hiring a specialist as the outcome of an unobservable underlying variable, $industry\ specialist_i^*$, which is determined by a vector of exogenous variables Z_i and a random component μ_i. In principle, no exclusion restriction is necessary to identify the model because, as discussed below, the second stage model will be augmented with the hazard ratio which is a nonlinear function of the variables (i.e., Z_i) included in the first-stage probit model. It is this non-linearity that identifies the second-stage model, even if the two sets of independent variables included in the first- and second-stage equations (X_i and Z_i) are identical (Heckman (1978);Wilde (2000)). The treatment rule is that if $industryspecialist_i^*$ exceeds zero, the acquiring firm employs an industry specialist advisor; otherwise, the acquiring firm uses a non-specialist advisor:

$$industryspecialist_i^* = Z_i\delta + \mu_i \tag{4}$$

where

$$industryspecialist_i = \begin{cases} 1 & if\, industryspecialist_i^* > 0 \\ 0 & if\, industryspecialist_i^* \leq 0 \end{cases}$$

Equation (4) is also known as the first-stage treatment equation. We obtain the probit estimates of this equation for the two types of advisors: $Prob(industry\ specialist_i = 1|Z_i) = \Phi(Z_i\delta)$; and $Prob(industryspecialist_i = 0|Z_i) = 1 - \Phi(Z_i\delta)$ where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. From these probit estimates, we compute the hazard ratio h_i for each observation as:

$$h_i = \begin{cases} \varphi(Z_i\delta)/\Phi(Z_i\delta)\ if industryspecialist_i = 1 \\ -\varphi(Z_i\delta)/[1-\Phi(Z_i\delta)]\ if industryspecialist_i = 0 \end{cases} \quad (5)$$

φ(·) is the density function of the standard normal distribution. According to Maddala (1983), augmenting equation (3) with the hazard ratio h_i allows for equation (6) below to be consistently estimated by OLS.

$$y_i = \gamma industryspecialsit_i + \lambda h_i + X_i\beta + \upsilon_i \quad (6)$$

This two-step estimator has been adopted to correct for self-selection bias in Song, et al. (2013) and Kisgen, Qian and Song (2009) in studying the value added by financial advisors in mergers and acquisitions. We restrict the endogeneity control solely to the industry specialist dummy because it captures the probability of using a specialist in the industry of the acquirer or the target or both. The significance of Lambda, the coefficient of h_i, indicates the presence of selection bias.

4.2. Bidder Abnormal Returns

4.2.1. Main Results

We examine the relation between advisor industry specialization and bidder abnormal returns using the two-step treatment procedure as described in Section 4.1.The dependent variable in the second stage (Equation 6) is bidder$CAR_{i,t}$, the cumulative abnormal return calculated over the event window (-1, +1) for the deal advised by $Invstment\ bank_i$ at time *t*.[5] We control forth deal and the bidder characteristics that have been shown in prior studies to be important in explaining acquirer CARs. We create six additional dummy variables: *public targets* × *payment include stock, public targets* × *all-cash, private targets* × *payment include stock, private targets* × *all-cash, subsidiary targets* × *all-cash, and*

[5] To test whether our results are robust to different event windows, we re-run the regressions on CAR (-2, +2), CAR (-5, +5), and CAR (0, +250). The results remain qualitatively the same as that reported for CAR (-1, +1).

subsidiary targets × *payment include stock* (the base group).These variables are used to capture the interaction effects of target public status and payment methods on bidder abnormal returns. The variables included are defined in Appendix A. Furthermore, we control for year fixed effects in all models however the coefficients are suppressed in result tables. If industry specialization enables investment banks to gain more sophisticated skill, knowledge and networks than their non-specialized peers, it should lead to better bidder CARs. We also split our full sample into merger and tender offers subsamples as prior research suggests that mergers and tender offers yield different returns to acquirer and target firms (Jensen and Ruback (1983);Loughran and Vijh (1997); Bradley, Desai and Kim (1988)). Table 2 presents the results for the analysis. Specification (1) reports the results for 'Industry Specialist' for the full sample.

A number of features are worth noting in the results presented. First, the regression coefficients of the selection equations (columns 1, 3 and 5 of Table 2) suggest that the probability of an acquirer using a specialist advisor is significantly higher when the firm is large and in stock-financed deals for all the selection models, except that the latter is insignificant for tender offers. The results in column (1) also show that when the transaction involves a foreign target or when the transaction size is larger, the probability of using a specialist advisor is significantly lower. These results appear to be largely driven by mergers. The significant coefficients of the variables show that they are important factors affecting an acquirer's choice of advisor and that the selection process is indeed endogenous.

In the outcome models (column 2, 4, and 6 of Table 2), we note that the size of the self-selection bias is substantial. We observe that the hazard ratio ("Lambda") is negative and statistically significant at the 1% level in the full and at the 5% level in the merger subsample. This suggests that endogeneity is present in these two models. The negative coefficients on the hazard ratios indicate that some unobservable factors simultaneously decrease the probability of using an industry specialist advisor and decrease acquirer abnormal returns. Failure to account for endogeneity can, therefore, lead to underestimation of the effect of specialist advisor on acquirer returns. The coefficients on industry specialist for the full sample and the merger subsample in Table 2are positive and statistically significant at the 1% and 5% levels respectively, which suggest that specialist advisors are able to deliver value to their acquirer clients in M&A transactions. Thus, by explicitly modeling selection in the first-stage regression, self-selection bias is largely minimized, leading to statistically significant coefficient estimates on industry specialist**.** Note that the hazard ratio is not statistically significant in the tender subsample and the coefficient on industry specialist is also statistically insignificant in this model. In order to ensure this finding is robust, we also run OLS regression (Equation 2) and in untabulated results we find the coefficient of industry specialization to be positive but statistically insignificant. Thus the endogeneity problem identified in the full sample seems to be driven primarily by the presence of mergers in the sample.

The coefficients on the control variables generally agree with extant literature. For example, we find that bidder's market capitalization has a negative and significant (at the 1% level in the full and merger subsample and10% in the tender offer subsample) impact on bidder abnormal returns, a finding that is consistent with Moeller, Schlingemann and Stulz (2004). The coefficient on bidder leverage is positive and significant at the 10% level only in the full sample. The interaction term, "*public targets × payment include stock"* negatively and significantly affects (at the 1% level) bidder abnormal returns in the full sample and the merger subsample whereas "*public targets × all-cash"* is also negative and significant (at the 1% level in the full and merger subsample).The results also show that "*private targets x payment include stock"* is negatively and significantly associated with bidder abnormal returns.

[Insert Table 2 here]

4.2.2. Cross- versus same-industry acquisitions

The findings in the previous section suggests that advisor industry specialization enhances acquiring firms' shareholder wealth. A related question that arises is whether this positive wealth effect of advisor industry specialization varies according to the industry relatedness. Intuitively, advisor industry-specific knowledge should be more valuable when acquirers undertake a cross industry rather than same industry deal becauseacquirers are likley to face more severe informaiton asymmetry when evaluating potential targets in unrelated sectors. Accordingly, one may expect the positive effect of advisor industry specialization to be more pronounced in cross-industry deals. We split the sample into cross and same industry deals and re-conduct the CAR analysis, using the same two-step treatment procedure. Table 3 documents the results of this exercise. We find that the industry specialist variable has a positive and highly significant (at the 1%) impact on acquirer returns in cross-industry deals (column (2)). The industry specialist variable for the same-industry subsample reported in column (4) is, however, statistically insignificant. The evidence presented supports the idea that advisors' industry-specifc knowledge is more important when acquirers venture into new industries.

[Insert Table 3 here]

4.2.3. Target- versus Acquirer-industry Specialists

If the economic value of advisor industry specialization primarily stems from cross-industry deals, a natural question is what type of industry do specialist advisors really matters? Compared with advisors specializing in the acquirer industry, target-industry specialists who have acquired substantial knowledge of the target's industry are arguably better able to help acquirer reduce the information asymmetry around the target. If so, they should play a more important role than acquirer-industry specialsits in generating value in a cross-industry acquisition. On the other hand, a general lack of understanding about the target's industry may make it realtively more difficult for the acquirer to assess whether a target advisor has provided any economically beneficial. This implies that the standard agency problem may arise, hampering the potential value of using a target industry specialist advisor. We address this issue by first spliting the general industry specialist dummy into two mutually exlcusive varaibles: target industry specialist, defined as a dummy variable equal to 1 if the advisor specializes in the target industry but not the acquirer industry; and 0 otherwise; and acquirer industry specialist, which indicates whether the advisor specializes in the acquirer industry but not the target industry. We then re-run the regressions of acquirer CAR on these two variables, respectively, for the full sample as well as the sample split by industry relatedness. The same two-step treatment procedure is employed to address the potential selection bias. To conserve space, we supressed the results from the first-stage regressions, which predicts the probability of using an advisor specializing in the target and the acquirer industry, respectively.

Table 4 reports the estimates for the second-stage equation of CAR. Columns (1), (2) and(3) estimate the impact of target industry specialist advisor on acquirer announcement abnormal returns for the full sample and the subsamples of cross and same industry deals, respectively. Surprisingly, we observe that the target industry specialist variable, though positive, is statistically insignificant in all the three models estimated. Thus, target industry specialization creates little or no value for acquirer clients even in cross-industry deals. By contrast, there is anincrease in acquirer CAR when an acquirer industry specialist advisor is hired (column (3)), and this effect primarily comes from cross-industry deals (columns (4) and (5)). This evidence is consistent with the notion that acquirers without adequate knowledge of a target's industry face greater agency problems. Advisors hired are likely to exert insufficient effort advising the deal if acquirer does not have a good understanding of the target's operating environment and strategy profiles. This problem appears, however, to some extent mitigated when the acquirer uses an advisor that is specializing in its own industry. One possible interpretation is that industry specialist advisors devote greater investment in networking with firms in the industry. This potentially increases the possibility of repeated dealings in the future, thus weakening the incentive to free ride on the clients.

[Insert Table 4 here]

4.3. Source of value creation

4.3.1. Deal premium

One way for industry specialist advisors to create value for their acquirer clients is to reduce the acquisition costs by using their industry-specific knowledge of the deal. We investigate this contention by examining the deal premiums paid to the target shareholders, defined as the percentage premium of offer price over the target price four weeks before the deal is announced. We limit the analysis to public deals because share price information is only available for listed targets. We use this variable as a dependent variable in the deal premium regressions. Following {Officer, 2003 #49}, we winsorize the percentage premium if the value is beyond the range of [0%, 2]. Table 5 presents the deal premium results after controlling for self-selection bias in the use of industry specialist using a two stage treatment procedure as outlined in Section 4.1.As premiums paid are likely to be influenced by the negotiation ability of the parties involved, we control for the target use of a specialist advisor and the use of top 8 investment bank by the target. We also control for other variables that can potentially influence the deal premium. The results for the full sample (column 2) show a negative and significant association between the use of a specialist and premium paid. This finding implies that industry specialist advisors have better negotiation skills thus preventing the bidder overpaying. We also find that premium is lower when the target employs a specialist advisor. Thus bidder advisors still have strong negotiation skills even after controlling for the target's use of a specialist advisor.

Partitioning the sample into merger and tender offer subsamples, we find that our results are driven by the merger subsample as the coefficient estimates on both industry specialist and target industry specialist are negative and statistically significant at the 1 percent level (column 4). We however do not find significant effects of industry specialist on the deal premium in the tender subsample. The results confirm the findings in the CARs analysis where we show that specialist advisors deliver value in the full sample and the merger subsample. This value creation is in part created by specialist advisors' ability to negotiate lower premiums and prevent overpaying for the target.

[Insert Table 5 here]

4.3.2. Total synergies

In this section we investigate whether specialist advisors add value to their acquirer clients by identifying targets with greater synergy. We explore this possibility by investigating the total synergy created in the transaction. We follow Golubov, et al. (2012) and define total synergies as the aggregate wealth gains made by both the bidder and the target, with wealth gains being a product of the three-day CARs and the market capitalization of the respective firms 11 days prior to the announcement date. Again, we control for endogeneity as outlined in Section 4.1 and provide the results for the two-step treatment procedure of total synergy created in Table 6. We focus the discussions on the second stage results as presented in columns 2, 4 and 6. In the full and the merger subsample, we find a positive and significant (5% level) association between the use of a specialist advisor and the synergies created in the transaction. Our results indicate that specialist advisors possess the ability to identify synergistic targets to the benefit of the bidder.

Combining the total synergy analysis with the premium results, we demonstrate that industry specialists create value for their acquirer clients by reducing acquisition costs and at the same time identifying more synergistic deals.

[Insert Table 6 here]

4.4. Completion Probability

In this section we explore whether industry specialist advisors are associated with higher completion rates. Here again we estimate equation (5) and control for potential selectivity. In the probit model, the dependent variable is set equal to 1 if a completed deal is advised by $Invstment\ bank_i$ at time *t*, and 0 otherwise. Bidders can self-select investment advisors that can potentially complete a deal, indicating potential selection bias in the probit model. We use the two-step treatment procedure to deal with potential endogeneity and report the results in Table 7. In the full sample and the merger subsample, the Lambda is positive and statistically significant indicating certain unobservable characteristic are positively correlated with the use of industry specialist as well as the completion probability. Our results show that specialist advisors are less likely to complete a deal in the full sample and the merger subsample but they have no measurable effect on the completion probability in tender offers. The results for the full sample and the merger subsample indicate that bad deals are more likely to be rejected when industry specialist advisor is present (Kisgen, et al. (2009)). Given the results in our premium analysis, it is also likely that the lower completion probability is caused by the lower premium offered in deals that are associated with an industry specialist.

[Insert Table 7 here]

4.5. Time to Completion

Results of examining the effect of advisor industry specialization on the time it takes to complete a deal are presented and discussed in this section.

After considering industry specialization theories described in section 2, we expect that relative industry specialization would improve advisors' efficiency in handling deals from their specialized domain and, therefore, be associated with shorter deal duration. It is also possible that bidders will approach investment advisors that have the potential to complete deals faster. This self-selection process signals potential endogeneity, making the OLS model unreliable. Consequently, we again use the two-step treatment procedure to control for endogeneity and report the results in Table 8. We use Equation (5) where the dependent variable is the time from the deal announcement date to its effective date, in units of 100 days. In the full sample and merger subsample, the hazard ratio, Lambda, is negative and statistically significant indicating that some unobserved characteristics decrease the time to complete a deal and simultaneously decrease the likelihood of using an advisor in a M&A transaction. Lambda is however positive and significant in the tender offer subsample. The hazard ratios also show that the degree of selection bias is high in these models. In the full sample and the merger subsample in Table 8, we find a positive and statistically significant relation between industry specialist and time to complete a deal, which is contrary to our prediction. The coefficient on bidder advisors' specialization level is positive and highly significant at the 1% level, suggesting that industry specialization elongates the time to completion in mergers. These results reflect the notion that industry specialist advisors are probably more careful in handling deals from their specialized industry, since these industries often constitute their core business and are thus important for their reputation. It is also possible that private discussions in mergers generally lengthen the acquisition process, especially if specialist advisors have different information sets on either side of the deal. However, the coefficient on the tender subsample is negative and statistically significant at the 1% level indicating that industry specialists take a significantly shorter time to complete tender offers. This is possible because tender offers do not require negotiations with the bidder's management team.

[Insert Table 8 here]

4.6. M&A Advisory Fees

M&A advisory fees may also be endogenously determined as acquirers can self-select specialist advisors on the basis of fee expectations. To the extent that self-selection is present in the data, results based on OLS estimates will not be reliable. Accordingly, we again correct for endogeneity using the two-step treatment procedure. We estimate equation (5) in which the dependent variable is the natural logarithm of advisory fees paid by the bidding firm to $Invstment\ bank_i$ at time t. The remaining variables have the same definitions as in $Equation$ (3). The sample used here includes completed transactions only because advisory fees are only reported by the SDC database when the deal succeeds.

We provide the results for the two-step treatment procedure in Table 9. Specifications (1), (3) and (5) provide the first stage results where the probability of using a specialist is determined and the outcome variable which is the fee regression results are provided in specifications (2), (4) and (6) for the full sample, merger and tender subsamples, respectively. These models include the hazard ratio as the control for selectivity. Again, the extent of the bias is large in the full sample and the merger subsample. Lambda is positive and statistically significant in the full sample and merger sample models indicating that some unobservable characteristics increase advisory fees charged by a specialist. After controlling for selectivity, we find a significant and negative relation between industry specialist and the advisory fee charged in the full sample and the merger subsample. These findings provide evidence that advisors are able to pass cost efficiencies achieved through economies of industry specialization onto their bidder clients. Fees charged in tender offers are not endogenously determined as the hazard ratio is statistically insignificant. In this model, industry specialization is not a statistically significant determinant of fees. In addition to bidder advisors' industry specialization, Table 9 shows many other interesting results. In line with prior research, fees are positively associated with the use of top 8 advisory firms, deal size, tender offer, bidder sigma and bidder run-up.

[Insert Table 9 here]

4.7. Additional Robustness Checks

To check whether our results are sensitive to our measurement of industry specialization, we first recompute the ARCA index using the 2-digit SIC codes and the Fama French 12 industry classification, given that investment banks are likely to specialize in a relatively broadly defined industry to maintain a stable market presence and also to maximize the benefits from economies of scale (Dunbar (2000)). We then replicate the analysis and find that the results remain essentially unchanged. We perform further robustness checks by remeasuring the ARCA index based on the number of deals advised by a bank in an industry. Compared with the value basis, the number basis may capture the situation where an investment bank has developed industry expertise through processing small but numerous deals (e.g. Balsam, et al. (2003); Benou, Gleason and Madura (2007)). We find the results to be qualitatively the same. Lastly, we change our rolling window to one year and three years, and we find our results are not sensitive to the choice of the length of the rolling window.

5. Conclusion

Inspired by the recent trend of investment banks' industry specialization, this paper examines the impact of advisor industry specialization on deal performance and the level of M&A advisory fees. Using a comprehensive sample of U.S. M&A transactions announced between 1985 and 2010, we show that advisor industry specialization has a significant and positive impact on acquirer CARs, holding all other factors constant. The positive impact of industry specialization is pronounced in cross-industry transactions. The value enhancement primarily comes from specialists' superior ability to reduce takeover premium and to identify more synergistic target, especially in merger deals. The use of industry specialists, however, is associated with lower completion probability, suggesting that industry specialization reduces a bidder advisors' ability to consummate certain deals successfully. There is also strong evidence suggesting that industry specialists are associated with longer time to complete a deal in the full sample and merger subsamples, but spend less time in completing tender offers. In regard to the pricing of M&A advisory service, industry specialization has a negative and significant impact on advisory fees in the full and the merger subsample, a finding that corroborates the cost efficiencies achieved by bidder advisors through economies of industry specialization. Overall, our results suggest that advisor industry specialization is economically desirable, for it enables financial advisors to deliver superior advice to their bidder clients at low costs.

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Appendix A Variable Definitions

Variable	Definition
Panel A: Dependent Variables and Industry Specialization	
CAR (-1, 1)	Cumulative abnormal returns of the acquiring firm stock over the event window (-1, +1) surrounding the announcement date. The return is calculated using the market model with the benchmark being the CRSP value-weighted index. The model parameters are estimated over the (-300, -91) period prior to the announcement. The CAR over the window (-1, +1) is winsorized at 1% and 99% in our analyses.
Complete	A dummy variable set equal to 1 if the deal is completed and 0 otherwise.
Speed	The time from the deal announcement date to its effective date measured in units of 100 days.
Log (Fees)	The natural logarithm of advisory fees paid by the bidding firms (completed deals only)
Takeover premium	A percentage premium of offer price over target market value 4 weeks prior to the deal announcement.
Advisor industry specialization	The relative degree of advisors' specialization in the acquirer (target) industry determined by the ARCA measure. It is calculated based on the total value of deals advised by an advisor in the acquirer (target) industry 5 years prior to the announcement date, where the industry is defined by the 3-digit SIC code.
Industry specialist advisor	A dummy variable is equal to 1 if the advisor is classified as a specialist if the ARCA value is greater than zero; and 0 otherwise
Panel B: Deal Characteristics	
Log (Deal Size)	The natural logarithm of the value of the transaction in millions of $US dollars (from Thomson Financial SDC)
Relative Size	The deal value divided by the market value of the bidding firm's equity one month prior to the announcement date (from CRSP)
Relatedness	A dummy variable setting to 1 if the bidder and the target are operating in the same industries with a common 2-digit SIC code and 0 otherwise (from Thomson Financial SDC).
Public Target	A dummy variable being 1 if the bid is for public target and 0 otherwise.

Private Target	A dummy variable being 1 if the bid is for private target and 0 otherwise.
Subsidiary Target	A dummy variable being 1 if the bid is for subsidiary target and 0 otherwise.
Foreign Target	A dummy variable being 1 if the bid is for foreign target and 0 otherwise.
All –Cash Deals	A dummy variable being 1 if the payment is pure cash and 0 otherwise.
Pmt. Incl. Stock	A dummy variable being 1 if the payment includes stock and 0 otherwise.
Tender Offer	A dummy variable equal to 1 if the deal is a tender offer and 0 otherwise.
Hostile	A dummy variable equal to 1 if the deal is classified as 'hostile' by Thompson Financial SDC and 0 otherwise.
Acq. Industry M&A (Targ. **Industry M&A)**	A control variable for M&A waves in the industry of the acquirer (target) in the previous year, where industry is classified by 3-digit SIC code. It equals the total value of all M&A transactions reported by SDC for each prior year and 3-digit SIC code over the book value of total assets of all Computstat firms in the same year and 3-digit SIC code.
Multiple Bidders	A dummy variable being 1 if there are multiple bidders and 0 otherwise (Kale et al. 2003).
Premium Offered	Takeover premium being the difference between the offer price and the target market value 4 weeks prior to the announcement, expressed as a percentage, form SDC.
Panel C: Bidder Characteristics	
Bidder Size	The market value of the bidding firm's equity 1 month prior to the announcement date in millions of $US dollars. The data is obtained from CRSP.
Tobin's Q	Market value of assets divided by book value of assets for the fiscal year prior to the acquisition. The market value of assets is equal to book value of assets plus market value of common stock minus book value of common stock minus balance sheet deferred taxes. The data is obtained from both CRSP and Compustat.
Run-up	Market-adjusted buy-and-hold returns of the bidder's stock over a 200-day window (-205, -6) from CRSP.
Sigma	Standard deviation of the market-adjusted daily returns of the bidder's stock over a 200-day

	window (-205, -6) from CRSP.
Leverage	The sum of long-term debt and short-term debt divided by the market value of total assets measured at the end of the fiscal year prior to the acquisition. The data is obtained from both CRSP and Compustat.
Free Cash Flow	Operating income before depreciation minus interest expense minus income tax plus changes in deferred taxes and investment tax credits minus dividends on both preferred and common share divided by the book value of total assets at the fiscal year-end before the announcement date from Computstat.

Table 1

Sample Descriptive Statistics by Type of Advisors

This table reports descriptive statistics of the key variables sorted by the type of advisors. The sample consists of 12,853 deals announced between January 1985 and December 2010, in which there is at least one investment bank advising either the acquirer or the target. The data is drawn from the Thomson Financial SDC database. Panels A to C illustrate the mean, median and number of observations ("N") for each variable for the full sample as well as for bidder advisors with and without acquirer-industry focus. The statistics for bidder advisors with and without target-industry focus are qualitatively similar to the results reported below but omitted for space consideration. Industry specialist advisors are designated using the ARCA measure and based on the value of deals advised by the advisor in the acquirer or target industry over 5 years prior to the announcement date. The industry is defined by 3-digit SIC code. Share price data for the bidding firms is obtained from CRSP while accounting data is downloaded from Computstat. Two-sample Wilcoxon rank-sum test is used to test the significance of differences in means and equality of medians for each variable sorted by the type of financial advisors.

	Full Sample (1)			Industry Specialists (2)			Non-industry Specialists (3)			Difference (2) – (3) in	
	Mean	Median	N	Mean	Median	N	Mean	Median	N	Mean	Median
Panel A: Dependent Variables											
CAR(-1, +1)	0.003	0.000	8266	0.000	-0.003	4481	0.007	0.002	3367	-0.007***	-0.005***
Premium Offered	1.431	2.000	3318	1.393	1.929	1823	1.459	2.000	1308	-0.067**	-0.071**
Advisory Fees (in $mil)	3.618	1.250	1886	4.180	1.500	958	3.471	1.450	791	0.709**	0.050
Completion Rate	0.928	1.000	12852	0.929	1.000	6665	0.930	1.000	5355	-0.001	0.000
Time to Complete (in units of 100 days)	1.009	0.790	11921	1.057	0.870	6190	0.948	0.710	4978	0.109***	0.160***
Panel B: Deal Characteristics											
Deal Value (in $mil)	684.029	135.000	12852	810.984	151.828	6665	614.123	140.000	5355	196.861***	11.828***
Relative Size	0.451	0.192	9131	0.403	0.170	4936	0.467	0.218	3723	-0.064***	-0.048***
Public Targets	0.365	-	12852	0.385	-	6665	0.344	-	5355	0.041***	-
Private Targets	0.304	-	12852	0.310	-	6665	0.288	-	5355	0.022***	-
Subsidiary Targets	0.323	-	12852	0.297	-	6665	0.360	-	5355	-0.063***	-
Foreign Targets	0.142	-	12852	0.118	-	6665	0.154	-	5355	-0.035***	-
Relatedness	0.601	-	12852	0.613	-	6665	0.589	-	5355	0.023***	-
Tender Offer	0.092	-	12852	0.082	-	6665	0.104	-	5355	-0.022***	-
Hostile Deal	0.018	-	12852	0.015	-	6665	0.023	-	5355	-0.008***	-
All-Cash	0.276	-	12852	0.262	-	6665	0.298	-	5355	-0.036***	-
Pmt. include Stock	0.389	-	12852	0.434	-	6665	0.337	-	5355	0.097***	-
Multiple Bidders	0.040	-	12842	0.042	-	6661	0.041	-	5351	0.001	-
Acq. Ind. M&A	-2.272	-2.184	12198	-2.346	-2.215	6393	-2.194	-2.119	5027	-0.151***	-0.096***
Targ. Ind. M&A	-2.169	-2.155	12179	-2.257	-2.205	6433	-2.056	-2.045	4963	-0.201***	-0.160**

Panel C: Bidder Characteristics											
Bidder Size (in $mil)	6861.037	787.534	9150	7858.925	939.825	4941	6191.661	725.170	3730	1667.264***	214.655***
Tobin's Q	2.436	1.534	7840	2.552	1.511	4251	2.316	1.574	3199	0.236**	-0.063*
Run-up	0.078	0.015	9201	0.086	0.021	4969	0.069	0.008	3746	0.016	0.012***
Free Cash Flow	0.052	0.085	7812	0.049	0.077	4198	0.058	0.094	3219	-0.010**	-0.017***
Leverage	0.147	0.104	7827	0.145	0.102	4247	0.151	0.109	3194	-0.006	-0.006**
Sigma	0.028	0.023	9202	0.028	0.023	4970	0.028	0.024	3746	0.000	-0.001**

Table 2

Two-step Treatment Procedure for Bidder CARs

This table reports the estimation results from a two-step treatment procedure for the bidder CARs for the full sample as well as the merger and tender subsamples. In each model, the first column shows the probit regression results of the first-stage selection equation, where the dependent variable is a dummy variable equal to 1 if a bidder hires an industry specialist advisor, and 0 otherwise. The results for the second-stage equation are shown in the second column for each model, where the dependent variable here is the CAR on the bidder's stock over the event window (-1, +1). The dummy variable 'Industry Specialist' is equal to 1 if the advisor is specializing in either the acquirer or the target industry or both; and 0 otherwise. The variable 'Lambda' is estimated from the first-stage equation and used as an additional regressor in the second-stage equation to adjust for self-selection bias. Other variables are defined in Appendix A. The z-statistics statistics in parentheses are adjusted for heteroskedasticity and bidder clustering. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. N denotes the number of observations.

	Full		Merger		Tender	
	(1)		(2)		(3)	
	Selection	Outcome	Selection	Outcome	Selection	Outcome
Industry Specialist		0.1392***		0.1145**		0.0821
		(3.0411)		(2.4925)		(1.1900)
Top 8		0.0041*		0.0015		0.0064
		(1.8512)		(0.6312)		(1.1550)
Ln(Bidder Size)	0.0740***	-0.0064***	0.0701***	-0.0057***	0.1281**	-0.0065*
	(5.3636)	(-3.9732)	(4.8160)	(-3.6428)	(2.3898)	(-1.8376)
Tobin's Q	0.0089	-0.0019***	0.0080	-0.0019***	-0.0021	-0.0030
	(1.1069)	(-2.8948)	(0.9738)	(-3.0652)	(-0.0460)	(-1.3192)
Free Cash Flow	-0.0813	-0.0194**	-0.0894	-0.0231***	-0.1136	0.0535
	(-0.7813)	(-2.2476)	(-0.8444)	(-2.8054)	(-0.1444)	(1.4170)
Leverage	0.0863	0.0185*	0.1054	0.0126	-0.5406	0.0098
	(0.7139)	(1.8843)	(0.8321)	(1.3020)	(-1.1473)	(0.3774)
Run-up	0.0182	-0.0064**	0.0086	-0.0069**	0.0945	-0.0230**
	(0.4716)	(-2.0814)	(0.2165)	(-2.3454)	(0.4786)	(-2.2620)
Sigma	-1.7765	0.3633***	-1.7676	0.3598***	9.6162	0.0044
	(-1.2597)	(3.1706)	(-1.1999)	(3.2429)	(1.5187)	(0.0107)
Ln(DealValue)	-0.0695***	0.0022	-0.0642***	0.0031**	0.0121	-0.0071**
	(-4.6730)	(1.3687)	(-4.0764)	(2.0170)	(0.2071)	(-2.2646)
Relative Size	0.0132	0.0038***	-0.0055	0.0043***	0.2388**	0.0034
	(0.7694)	(2.7117)	(-0.2928)	(3.1208)	(2.2432)	(0.9065)
Relatedness	0.0638*	-0.0011	0.0666*	0.0009	-0.0349	-0.0008
	(1.8123)	(-0.3637)	(1.7868)	(0.2873)	(-0.2895)	(-0.1233)
Pub. Targ. * All-Cash		-0.0104***		-0.0114**		0.0063
		(-2.6388)		(-2.3462)		(0.9755)
Pub. Targ. * Pmt. incl. Stock		-0.0561***		-0.0569***		-0.0156

		(-12.7392)		(-12.7600)		(-1.4115)
Priv. Targ. * All-Cash		0.0022		-0.0071*		0.1879***
		(0.5315)		(-1.6522)		(6.9075)
Priv. Targ. * Pmt. incl. Stock		-0.0140***		-0.0129***		-0.1185***
		(-2.9658)		(-2.7144)		(-2.8382)
Sub. Targ. * All-Cash		0.0069*		0.0043		-0.0000
		(1.9307)		(1.1693)		(-0.0011)
Pmt. Incl. stock	0.2683***		0.2655***		0.1767	
	(7.2829)		(6.9547)		(1.0314)	
Tender	0.0570	0.0083				
	(0.9426)	(1.5894)				
Hostile	-0.1239	-0.0138	-0.4379*	0.0050	0.0912	-0.0191*
	(-0.9276)	(-1.2470)	(-1.9553)	(0.2717)	(0.4733)	(-1.8662)
Foreign Target	-0.2288***	0.0084	-0.2565***	0.0077	0.1284	-0.0008
	(-4.7073)	(1.4621)	(-4.8887)	(1.2643)	(0.8836)	(-0.0969)
Multiple Bidders	0.0842	0.0028	-0.0877	-0.0038	0.2169	-0.0085
	(1.0131)	(0.4053)	(-0.8077)	(-0.4506)	(1.4112)	(-0.8599)
Ln(Acq. Industry M&A)	-0.0197	-0.0000	-0.0204	-0.0001	0.0096	-0.0016
	(-1.6065)	(-0.0471)	(-1.5753)	(-0.1118)	(0.2154)	(-0.7096)
Ln(Targ. Industry M&A)	-0.0174	0.0016	-0.0213*	0.0014	-0.0009	-0.0010
	(-1.4881)	(1.6364)	(-1.7202)	(1.3976)	(-0.0234)	(-0.4858)
Lambda		-0.0874***		-0.0729**		-0.0496
		(-3.0854)		(-2.5651)		(-1.1798)
Intercept	-0.6286**	0.0365	-0.5369*	0.0163	-3.7511***	0.2276***
	(-2.1677)	(1.3742)	(-1.7180)	(0.5945)	(-3.5957)	(2.8921)
N	6269	6269	5668	5668	601	601

Table 3

Two-step Treatment Procedure for the Cross- versus Same-industry Analysis

This table presents the results from a two-step treatment procedure for the bidder CARs for the sample split by industry relaedness. In each model, the first column shows the probit regression results of the first-stage selection equation, where the dependent variable is a dummy variable equal to 1 if a bidder hires an industry specialist advisor, and 0 otherwise. The results for the second-stage equation are shown in the second column for each model, where the dependent variable here is the CAR on the bidder's stock over the event window (-1, +1). The dummy variable 'Industry Specialist' is equal to 1 if the advisor is specializing in either the acquirer or the target industry or both; and 0 otherwise. The variable 'Lambda' is estimated from the first-stage equation and used as an additional regressor in the second-stage equation to adjust for self-selection bias. Other variables are defined in Appendix A. The z-statistics statistics in parentheses are adjusted for heteroskedasticity and bidder clustering. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. N denotes the number of observations.

	Cross Industry		Same Industry	
	(1)	(2)	(3)	(4)
	Selection	Outcome	Selection	Outcome
Industry Specialist		0.0944***		0.0215
		(7.8092)		(0.6725)
Top 8		0.0060		0.0017
		(1.4940)		(0.6361)
Ln(Bidder Size)	0.0967***	-0.0060***	0.0736***	-0.0040***
	(4.2739)	(-3.7020)	(3.5481)	(-2.6504)
Tobin's Q	0.0151	-0.0039***	0.0044	-0.0003
	(1.0040)	(-3.6351)	(0.3772)	(-0.2669)
Free Cash Flow	0.2422	-0.0348**	-0.2034	-0.0224
	(1.0485)	(-2.1905)	(-1.2405)	(-1.3556)
Leverage	0.3558	0.0105	-0.0479	0.0211**
	(1.6269)	(0.7037)	(-0.2866)	(2.0749)
Run-up	-0.0506	-0.0031	0.0510	-0.0074
	(-0.7522)	(-0.6206)	(1.0031)	(-1.5461)
Sigma	6.3295**	-0.0982	-4.6688**	0.4215**
	(2.2700)	(-0.3994)	(-2.4661)	(2.4559)
Ln(DealValue)	-0.0364	-0.0010	-0.0809***	0.0014
	(-1.4143)	(-0.5814)	(-3.6892)	(0.7959)
Relative Size	-0.0096	0.0058***	0.0426	0.0024
	(-0.5056)	(4.6279)	(1.4536)	(0.7891)
Pub. Targ. * All-Cash		-0.0098*		-0.0098**
		(-1.6635)		(-2.3989)
Pub. Targ. * Pmt. incl. Stock		-0.0510***		-0.0475***
		(-8.9502)		(-9.5278)
Priv. Targ. * All-Cash		0.0142*		-0.0118**

		(1.7132)		(-2.4043)
Priv. Targ. * Pmt. incl. Stock		-0.0110		-0.0035
		(-1.5541)		(-0.6268)
Sub. Targ. * All-Cash		0.0073		0.0035
		(1.2940)		(0.8248)
Pmt. Incl. stock	0.1981***		0.3077***	
	(3.0365)		(6.2451)	
Tender	-0.0658	0.0154**	0.1108	0.0015
	(-0.7213)	(2.1536)	(1.3617)	(0.2985)
Hostile	0.1164	-0.0340***	-0.1405	-0.0111
	(0.5537)	(-2.6976)	(-0.8119)	(-1.1474)
Foreign Target	-0.1243	-0.0016	-0.2723***	0.0010
	(-1.5389)	(-0.2925)	(-4.2450)	(0.2033)
Multiple Bidders	0.3755**	0.0113	-0.1389	-0.0048
	(2.3031)	(0.9978)	(-1.3230)	(-0.7641)
Ln(Acq. Industry M&A)	-0.0001	-0.0006	-0.0166	-0.0018
	(-0.0059)	(-0.4708)	(-0.6339)	(-1.1630)
Ln(Targ. Industry M&A)	0.0030	-0.0002	-0.0263	0.0015
	(0.1960)	(-0.2087)	(-1.0584)	(1.0194)
Lambda		-0.0587***		-0.0152
		(-7.1036)		(-0.7644)
Intercept	-1.6431***	0.0881**	-0.4026	0.0525**
	(-3.1103)	(2.2897)	(-1.0264)	(2.0905)
N	2123	2123	4146	4146

Table 4

Two-step Treatment Procedure for the Advisor Industry Focus Analysis

This table examines the impact of advisor industry focus on the bidder CARs for the full sample as well as for the sample split by industry relaedness. In each specification, the dependent variable is the bidder CAR (-1, +1). The first-stage model estimates the probability that a bidder hires an advisor specializing in a particular industry (i.e., the industry of acquirer or that of target or both industries). To conserve space, the results from the first-stage regressions are omitted. The first three columns present the results from the second-stage regressions on ‘Acq. Industry Specialist’, which is a dummy variable indicating whether the advisor is a specialist in the acquirer industry but not the target industry, for the full sample, the cross- and same-industry subsample, respectively. Columns (4) and (6) replicate the analysis using ‘Targ. Industry Specialist’, which equal to 1 if the advisor is a specialist in the target industry but not the acquirer industry; and 0 otherwise. Each seond-stage models is augmented with the variable ‘Lambda’ estimated from the first-stage equation to adjust for self-selection bias. Other variables are defined in Appendix A. The z-statistics statistics in parentheses are adjusted for heteroskedasticity and bidder clustering. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. N denotes the number of observations.

	Full (1)	Cross-industry (2)	Same-industry (3)	Full (4)	Cross-industry (5)	Same-industry (6)
Targ. Industry Specialist	0.0052	0.0139	0.0057			
	(1.0312)	(1.4069)	(0.6554)			
Acq. Industry Specialist				0.1046***	0.1227***	-0.0073
				(13.7764)	(17.4024)	(-0.4526)
Top 8	0.0042	0.0060	0.0019	0.0048*	0.0069*	0.0016
	(1.5702)	(1.4672)	(0.6722)	(1.9193)	(1.7957)	(0.5927)
Ln(Bidder Size)	-0.0027***	-0.0025*	-0.0034***	-0.0042***	-0.0054***	-0.0034***
	(-3.1602)	(-1.9431)	(-2.9369)	(-4.3526)	(-3.3512)	(-2.9183)
Tobin's Q	-0.0014	-0.0036***	-0.0003	-0.0012	-0.0029***	-0.0003
	(-1.6042)	(-3.5091)	(-0.2509)	(-1.2500)	(-2.6297)	(-0.2584)
Free Cash Flow	-0.0239**	-0.0308**	-0.0240	-0.0219*	-0.0232	-0.0243
	(-2.1450)	(-2.3976)	(-1.5103)	(-1.7483)	(-1.3229)	(-1.5328)
Leverage	0.0227**	0.0206	0.0208**	0.0167*	0.0149	0.0210**
	(2.5496)	(1.5244)	(2.0843)	(1.8535)	(0.9989)	(2.0873)
Run-up	-0.0054	-0.0048	-0.0069	-0.0069*	-0.0043	-0.0067
	(-1.5367)	(-1.0277)	(-1.4677)	(-1.9333)	(-0.9019)	(-1.4366)
Sigma	0.2847**	0.0997	0.3851**	0.2889**	0.1512	0.3880**
	(2.3022)	(0.4712)	(2.3980)	(2.1886)	(0.6218)	(2.4121)
Ln(Deal Value)	-0.0012	-0.0026	0.0007	-0.0004	-0.0008	0.0008
	(-0.9539)	(-1.5860)	(0.5235)	(-0.3858)	(-0.4530)	(0.5696)
Relative Size	0.0045***	0.0055***	0.0028	0.0046***	0.0060***	0.0027
	(3.0511)	(3.9392)	(0.9665)	(2.8622)	(4.0094)	(0.9635)
Relatedness	0.0027			0.0139***		
	(1.1663)			(5.4073)		

Pub. Targ. * All-Cash	-0.0124***	-0.0111*	-0.0103**	-0.0112***	-0.0091	-0.0101**
	(-2.9721)	(-1.8587)	(-2.5107)	(-2.8886)	(-1.5817)	(-2.4814)
Pub. Targ. * Pmt. incl. Stock	-0.0448***	-0.0448***	-0.0456***	-0.0450***	-0.0489***	-0.0456***
	(-15.5018)	(-8.5403)	(-13.0882)	(-14.7980)	(-8.6320)	(-13.0314)
Priv. Targ. * All-Cash	-0.0000	0.0140*	-0.0125**	0.0000	0.0116	-0.0123**
	(-0.0036)	(1.6680)	(-2.5414)	(0.0059)	(1.5442)	(-2.5176)
Priv. Targ. * Pmt. incl. Stock	-0.0026	-0.0050	-0.0016	-0.0028	-0.0095	-0.0017
	(-0.6951)	(-0.7466)	(-0.3637)	(-0.7357)	(-1.4187)	(-0.3786)
Sub. Targ. * All-Cash	0.0045	0.0064	0.0030	0.0044	0.0042	0.0032
	(1.3017)	(1.1310)	(0.7181)	(1.3081)	(0.7766)	(0.7512)
Tender	0.0104	0.0136*	0.0022	0.0079	0.0111*	0.0023
	(1.6448)	(1.8945)	(0.4501)	(1.5825)	(1.6914)	(0.4661)
Hostile	-0.0212**	-0.0286***	-0.0126	-0.0185**	-0.0304**	-0.0124
	(-2.4837)	(-2.7612)	(-1.3267)	(-2.2195)	(-2.0872)	(-1.3053)
Foreign Targ.	-0.0040	-0.0070	-0.0013	-0.0013	0.0008	-0.0013
	(-1.3202)	(-1.4006)	(-0.3464)	(-0.4153)	(0.1491)	(-0.3401)
Multiple Bidders	0.0071	0.0250**	-0.0060	0.0030	0.0108	-0.0062
	(0.7250)	(1.9660)	(-1.0009)	(0.4600)	(1.2486)	(-1.0330)
Ln(Acq. Industry M&A)	-0.0011	-0.0005	-0.0019	-0.0015*	-0.0008	-0.0019
	(-1.3628)	(-0.4584)	(-1.2889)	(-1.7492)	(-0.6250)	(-1.2570)
Ln(Targ. Industry M&A)	0.0007	-0.0001	0.0013	0.0004	0.0003	0.0013
	(0.9477)	(-0.0871)	(0.8916)	(0.4490)	(0.2388)	(0.9278)
Lamda	-0.0021	-0.0042	-0.0039	-0.0554***	-0.0710***	0.0063
	(-1.2709)	(-0.9591)	(-1.2894)	(-13.0240)	(-10.4249)	(0.8068)
Intercept	0.0709***	0.0819**	0.0599***	0.0683***	0.0859**	0.0591***
	(3.4468)	(2.5756)	(2.7058)	(3.2478)	(2.2450)	(2.6777)
N	6269	2123	4146	6269	2123	4146

Table 5

Two-step Treatment Regression for Takeover Premiums

This table reports the results from a two-step treatment procedure for takeover premium for the public deals in the full sample as well as the merger and tender offer subsamples. Takeover premium is computed as a percentage premium of offer price over target market value 4 weeks prior to the deal announcement. Ln(Targ. M/B) is the natural logarithm of a ratio of the market value of equity relative to the book value of equity of target for the prior fiscal year, where the market value of target equity is calculated as one month before the announcement date. A bidder (target) advisor's industry specialization is measured using the ARCA method which is based on the value of deals advised by the bank in either the acquirer's industry (acquirer-industry focus) or the target firm's industry (target-industry focus) 5 years prior to the announcement date. Industry is classified by 3 digit SIC code. A cut-off of zero ARCA value is used to classify an advisor as industry specialist. In each specification, the first-stage model estimates the probability that a bidder hires an industry specialist advisor. In the second-stage regression of premium, the model is augmented by 'Lambda', which is obtained from the first-stage regression and included to adjust for self-selection bias. Other variables are defined in Appendix A. The z-statistics in parentheses are adjusted for heteroskedasticity and bidder clustering. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. N denotes the number of observations.

	Full		Merger		Tender	
	(1)		(2)		(3)	
	Selection	Outcome	Selection	Outcome	Selection	Outcome
Industry Specialist		-0.6856***		-0.6894***		0.3470
		(-4.7499)		(-4.6285)		(1.0268)
Target Industry Specialist		-0.1865***		-0.2028***		-0.1116
		(-5.0491)		(-4.9183)		(-1.3136)
Top 8		-0.0116		-0.0096		-0.0132
		(-0.2701)		(-0.2008)		(-0.1440)
Target Top 8		0.0199		0.0206		-0.0122
		(0.4735)		(0.4195)		(-0.1604)
All Cash		0.0332		0.0652		-0.0284
		(0.6161)		(0.9150)		(-0.3254)
Tender		0.1146**				
		(2.1265)				
Toehold		-0.2176		-0.1928		-0.0705
		(-0.9032)		(-0.4480)		(-0.3393)
Ln(Deal Value)	-0.0715	-0.1757***	-0.0189	-0.1507***	-0.1432	-0.1536***
	(-1.4996)	(-6.7321)	(-0.3023)	(-4.1248)	(-1.0664)	(-2.5955)
Relative Size	0.0297	0.0631**	-0.1230	-0.0162	0.3613*	0.0284
	(0.4267)	(2.0360)	(-0.8853)	(-0.2074)	(1.8185)	(0.6797)
Relatedness	0.0629	-0.0351	0.0575	-0.0516	-0.0012	0.0799
	(0.7036)	(-0.7523)	(0.5767)	(-0.9802)	(-0.0056)	(0.9179)
Foreign Target	-0.2646	0.1146	-0.1485	0.2183	-0.5026	0.1900
	(-0.9475)	(0.6278)	(-0.3999)	(0.9276)	(-0.8194)	(0.7417)
Hostile	0.0068	0.0984	-0.3058	0.1953	0.3303	-0.0696
	(0.0339)	(0.8553)	(-0.7737)	(0.8338)	(1.0542)	(-0.4580)

Multiple Bidders	-0.0877	-0.0406	-0.1542	-0.0375	0.3989	-0.0994
	(-0.6260)	(-0.6971)	(-0.9024)	(-0.5048)	(1.2338)	(-0.9127)
Ln(Targ. M/B)		-0.0779***		-0.0955***		-0.0677
		(-2.8621)		(-3.0773)		(-1.2100)
Ln(Bidder Size)	0.0519	0.0705***	-0.0131	0.0471	0.2842**	0.0272
	(1.1335)	(2.9477)	(-0.2107)	(1.3464)	(2.4224)	(0.6569)
Tobin's Q	0.0419***	0.0263***	0.0419***	0.0275***	0.0247	0.0020
	(2.6265)	(2.8515)	(2.5913)	(2.8797)	(0.4220)	(0.0749)
Free Cash Flow	-0.8902***		-1.0237***		-0.6065	
	(-3.0670)		(-3.4852)		(-0.4388)	
Leverage	0.2389		0.4210		-0.7308	
	(0.8931)		(1.4308)		(-0.7998)	
Run-up	-0.0461		-0.0189		-0.2361	
	(-0.7453)		(-0.2850)		(-0.5922)	
Sigma	-12.0323***		-14.2869***		16.4065	
	(-3.7436)		(-4.1377)		(1.5439)	
Pmt. Incl. stock	0.2765***		0.2789***		0.3897	
	(3.3210)		(2.6644)		(1.5164)	
Ln(Acq. Industry M&A)	-0.0392		-0.0267		-0.0552	
	(-1.3260)		(-0.8504)		(-0.5202)	
Ln(Targ. Industry M&A)	-0.0090		-0.0232		0.1878**	
	(-0.3180)		(-0.7642)		(2.2764)	
Lambda		0.4051***		0.4119***		-0.2559
		(4.8320)		(4.8690)		(-1.2464)
Intercept	0.3721	4.7344***	0.8048	4.9434***	-2.8430	4.3773***
	(0.4883)	(13.7163)	(0.9934)	(12.6914)	(-1.5461)	(5.6676)
N	1304	1304	1086	1086	218	218

Table 6

Two-step Treatment Procedure for Total Synergies

This table reports the results from the two-step treatment procedure for total synergies for public acquisitions in the full sample as well as the merger and tender offer subsamples. Total synergy is computed as the sum of the dollar gain of the acquirer and the target, with dollar gain a product of CAR (-1, +1) and the respective firms' market capitalization 4 weeks before the announcement. Advisor industry specialization is measured using the ARCA method based on the value of deals advised by the bank in an industry 5 years prior to the announcement date. Industry is classified by 3 digit SIC code. A cut-off of zero ARCA value is used to classify an advisor as industry specialist. In each specification, the first-stage model estimates the probability that a bidder hires an industry specialist advisor. In the second-stage regression of total synergies, the model is augmented by 'Lambda', which is obtained from the first-stage regression and included to adjust for self-selection bias. Other variables are defined in Appendix A. The z-statistics statistics are shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. N denotes the number of observations.

	Full		Merger		Tender	
	(1)		(2)		(3)	
	Selection	Outcome	Selection	Outcome	Selection	Outcome
Industry Specilast		2735.9869**		3174.5972**		392.2101
		(2.2519)		(2.3335)		(0.3761)
Top 8		67.5130		11.9563		450.2307***
		(0.7622)		(0.1153)		(3.5339)
Ln(Bidder Size)	0.0609**	-34.8174	0.0338	-4.1899	0.1262*	-55.5868
	(2.0801)	(-0.9819)	(1.0011)	(-0.1020)	(1.7102)	(-0.8673)
Tobin's Q	0.0408**	-80.8679***	0.0384**	-81.4616***	0.0795	-93.1823*
	(2.4883)	(-2.9862)	(2.2430)	(-2.7156)	(1.1514)	(-1.7963)
Free Cash Flow	-0.3821*	516.1522	-0.4636**	789.3217	-0.2197	-431.4011
	(-1.7154)	(1.2106)	(-2.0018)	(1.5451)	(-0.1846)	(-0.5191)
Leverage	0.0407	172.0279	0.1975	87.9708	-0.6058	-300.0109
	(0.1675)	(0.4446)	(0.7361)	(0.1867)	(-0.9159)	(-0.5779)
Run-up	-0.0353	-9.7967	0.0119	-108.1008	-0.1957	245.8541
	(-0.4806)	(-0.0822)	(0.1517)	(-0.7948)	(-0.7173)	(1.1434)
Sigma	-8.9077***	15938.1506**	-10.5066***	21649.6313***	10.8293	672.4149
	(-3.1685)	(2.5154)	(-3.3428)	(2.6567)	(1.3471)	(0.0972)
Ln(DealValue)	-0.0581*		-0.0529		0.0449	
	(-1.7997)		(-1.4420)		(0.5152)	
Relative Size	0.1183**	-91.7639	0.0965*	-106.2599	0.1761	-28.3487
	(2.5732)	(-1.4758)	(1.6457)	(-1.2510)	(1.3333)	(-0.4991)
Relatedness	0.1034	-102.1728	0.0840	-132.3073	-0.0567	250.0138**
	(1.4754)	(-0.8247)	(1.0620)	(-0.8908)	(-0.3168)	(2.0065)
Pmt. incl. Stock	0.2495***	-377.3559**	0.1822**	-421.8381**	0.2488	343.3746*
	(3.3865)	(-2.3325)	(1.9708)	(-2.3646)	(1.0181)	(1.6769)
Tender		-33.9516				

		(-0.2705)				
Hostile	-0.0378	217.5979	-0.2597	466.2327	0.2598	182.9332
	(-0.2019)	(0.7051)	(-0.8679)	(0.8370)	(0.9075)	(0.8239)
Foreign Target	-0.1925	322.0455	-0.1993	99.9320	-0.1318	632.0182**
	(-0.9428)	(0.9296)	(-0.7567)	(0.2049)	(-0.3376)	(2.3010)
Multiple Bidders	-0.1696	372.0702*	-0.2765*	585.2747*	0.0892	-235.0366
	(-1.4011)	(1.7056)	(-1.8793)	(1.8929)	(0.3615)	(-1.2938)
Ln(Acq. Industry M&A)	-0.0459*		-0.0419		-0.0026	
	(-1.8401)		(-1.5188)		(-0.0373)	
Ln(Targ. Industry M&A)	-0.0151		-0.0283		0.0485	
	(-0.6648)		(-1.1093)		(0.8783)	
Lambda		-1658.5580**		-1911.5821**		-274.7784
		(-2.2139)		(-2.2844)		(-0.4334)
Intercept	-0.2823	-812.3259	-0.2520	-882.3872	0.6833	-550.4423
	(-0.3494)	(-0.6021)	(-0.2680)	(-0.5212)	(0.0027)	(-0.3976)
N	1791	1791	1474	1474	317	317

Table 7
Two-step Treatment Procedure for Completion Probability

This table reports the estimation results of a two-step treatment procedure for the completion probability for the full sample as well as the merger and tender subsamples. In eachmodel, the first column shows the probit regression results of the first-stage selection equation, where the dependent variable is a dummy variable equal to 1 if a bidder hiresan industry specialist advisor, and 0 otherwise; while the second column estimates the probit regression results for the second-stage equation, where the dependent variable is the probability of deal completion. The dummy variable 'Industry Specialist' is equal to 1 if the advisor is specializing in either the acquirer or the target industry or both; and 0 otherwise. The variable 'Lambda' is estimated from the first-stage equation and used as an additional regressor in the second-stage equation to adjust for self-selection bias. Other variables are defined in Appendix A. The z-statistics statistics in parentheses are adjusted for heteroskedasticity. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. N denotes the number of observations.

	Full		Merger		Tender	
	(1)		(2)		(3)	
	Selection	Outcome	Selection	Outcome	Selection	Outcome
Industry Specialist		-0.7861*		-1.2319***		0.3437
		(-1.8200)		(-47.4000)		(0.5300)
Top 8		0.0849		0.0104		0.1261
		(1.4400)		(0.7700)		(0.6900)
Ln(Bidder Size)	0.0743***	0.1177***	0.0684***	0.0146	0.1338**	0.2440**
	(5.3800)	(4.9300)	(4.7300)	(1.0800)	(2.4300)	(2.4600)
Tobin's Q	0.0086	-0.0006	0.0076	-0.0006	-0.0035	0.0025
	(1.0700)	(-0.0500)	(0.9200)	(-0.2400)	(-0.0800)	(0.0400)
Free Cash Flow	-0.0790	-0.0089	-0.0853	-0.0027	-0.1247	0.8801
	(-0.7600)	(-0.0600)	(-0.8100)	(-0.0900)	(-0.1600)	(0.9400)
Leverage	0.0866	0.2485	0.1026	0.0205	-0.5513	1.6194**
	(0.7200)	(1.2700)	(0.8200)	(0.5100)	(-1.1600)	(2.2800)
Run-up	0.0169	0.0800	0.0151	0.0266	0.0914	-0.0689
	(0.4400)	(1.2100)	(0.3800)	(1.2500)	(0.4600)	(-0.2800)
Sigma	-1.6978	-3.6258*	-2.2301	-1.3338	9.4535	-7.9886
	(-1.2000)	(-1.7400)	(-1.5200)	(-1.5700)	(1.4900)	(-0.9500)
Ln(Deal Value)	-0.0686***	-0.1665***	-0.0636***	-0.0253	0.0096	-0.3074***
	(-4.6100)	(-6.0500)	(-4.0700)	(-1.3200)	(0.1600)	(-3.2400)
Relative Size	0.0131	0.0088	-0.0077	-0.0250***	0.2579**	0.1362
	(0.7600)	(0.4000)	(-0.4300)	(-4.2800)	(2.2700)	(1.2500)
Relatedness	0.0614*	0.0922	0.0703*	0.0252	-0.0360	0.0811
	(1.7500)	(1.6100)	(1.8900)	(1.3300)	(-0.3000)	(0.4700)

Pub. Targ. * All-Cash		-0.2844***		-0.0752		
		(-3.0100)		(-1.5800)		
Pub. Targ. * Pmt. incl. Stock		-0.0873		-0.0149		
		(-1.0300)		(-0.8900)		
Priv. Targ. * All-Cash		0.1741		0.0285		
		(1.2900)		(0.8000)		
Priv. Targ. * Pmt. incl. Stock		0.2960***		0.0543		
		(3.0200)		(1.5100)		
Sub. Targ. * All-Cash		0.3047**		0.0528		
		(2.4600)		(1.3600)		
Pmt. Incl. stock	0.2629***		0.2657***		0.1824	-0.0900
	(7.2800)		(7.0700)		(1.0600)	(-0.4200)
Tender		0.4216***				
		(3.8200)				
Hostile	-0.1116	-1.3363***	-0.4219**	-1.3315***	0.0767	-1.2829***
	(-0.8400)	(-8.0900)	(-1.9600)	(-24.6300)	(0.4000)	(-5.9200)
Foreign Targ.	-0.2245***	-0.2355***	-0.2554***	-0.0534	0.1415	-0.4031**
	(-4.6300)	(-2.8900)	(-4.9000)	(-1.5000)	(0.9600)	(-2.0800)
Multiple Bidders	0.1027	-1.2054***	-0.0530	-1.2701***	0.1980	-1.1086***
	(1.2700)	(-7.8700)	(-0.4900)	(-49.1400)	(1.2700)	(-6.2800)
Ln(Acq. Industry M&A)	-0.0195	-0.0107	-0.0187	-0.0028	0.0112	0.0486
	(-1.5800)	(-0.5400)	(-1.4600)	(-0.6600)	(0.2500)	(0.7700)
Ln(Targ. Industry M&A)	-0.0179	0.0190	-0.0244**	0.0045	-0.0009	-0.0838
	(-1.5200)	(0.9700)	(-1.9800)	(0.9600)	(-0.0200)	(-1.4300)
Lambda		0.5156**		0.7044***		-0.2479
		(1.9800)		(237.5100)		(-0.5800)
Intercept	-0.6394**	3.6810***	-0.5246*	2.2647***	-3.9065***	2.2042
	(-2.2000)	(5.4600)	(-1.6900)	(10.5000)	(-3.7600)	(1.6300)
N	6592	6592	5954	5954	638	638

Table 8
Two-step Treatment Procedure for Time to Completion

This table presents the estimation results of the two-step treatment procedure for the time to complete using the subsamples consisting of public, private, subsidiary acquisitions announced from 1985 to 2010. The dependent variable is time to complete measured as the time between the announcement and the effective dates in the unit of 100 days. The first-stage selection equation in each model estimates the probability that a bidder uses an industry specialist advisor for a particular type of transaction using the same explanatory variables as in Table V. The second-stage equation estimates time to complete and is augmented by an additional regressor 'Lambda'obtained from the first-stage equationto adjust for self-selection bias.The dummy variable 'Industry Specialist', is equal to 1 if the advisor is specializing in the acquirer industry, the target industry or both; and 0 otherwise. Other variables are defined in Appendix A. The z-statistics statistics in parentheses are adjusted for heteroskedasticity and bidder clustering. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. N denotes the number of observations.

	Full		Merger		Tender	
	(1)		(2)		(3)	
	Selection	Outcome	Selection	Outcome	Selection	Outcome
Industry Specialist		1.3671***		1.4061***		-1.1055***
		(6.5823)		(6.7626)		(-7.4613)
Top 8		0.0219		0.0233		-0.0806
		(0.7704)		(0.7582)		(-1.3987)
Ln(Bidder Size)	0.0804***	-0.0765***	0.0744***	-0.0827***	0.1352***	0.0788***
	(5.0997)	(-5.4471)	(4.5424)	(-5.5177)	(2.7622)	(2.6600)
Tobin's Q	0.0041	-0.0206***	0.0032	-0.0197***	-0.0163	-0.0193
	(0.4841)	(-3.1247)	(0.3681)	(-2.8739)	(-0.3749)	(-0.7678)
Free Cash Flow	0.0309	-0.5247***	0.0212	-0.5084***	-0.5185	-0.4587
	(0.2622)	(-3.9100)	(0.1806)	(-3.7794)	(-0.5914)	(-0.9635)
Leverage	-0.0057	0.5875***	0.0040	0.6109***	-0.8105*	-0.0854
	(-0.0414)	(4.2420)	(0.0278)	(4.0729)	(-1.6959)	(-0.2662)
Run-up	0.0362	0.0157	0.0261	0.0158	0.1201	-0.1061
	(0.9123)	(0.4024)	(0.6408)	(0.3891)	(0.6551)	(-0.6757)
Sigma	-1.4972	-4.5267***	-1.4406	-4.3924***	5.2864	3.3274
	(-0.9905)	(-3.3335)	(-0.9065)	(-3.0303)	(0.7883)	(0.8406)
Ln(DealValue)	-0.0688***	0.1331***	-0.0640***	0.1395***	-0.0113	0.0393
	(-4.0478)	(8.7814)	(-3.7318)	(8.6086)	(-0.2071)	(1.0002)
Relative Size	0.0275	0.0249	0.0095	0.0313	0.3411***	0.1023***
	(1.3315)	(1.6064)	(0.3827)	(1.5325)	(2.7788)	(4.9128)
Relatedness	0.0905**	0.0924**		0.0953**	0.0509	0.1416*
	(2.3835)	(2.5125)		(2.3740)	(0.4343)	(1.8977)
Pub. Targ. * All-Cash		0.2550***		0.3814***		-0.1170**
		(5.7756)		(7.4108)		(-2.0126)
Pub. Targ. * Pmt. incl. Stock		0.4290***		0.4130***		0.7013***
		(10.5381)		(9.8946)		(4.3949)
Priv. Targ. * All-Cash		0.0091		-0.0007		1.0409***

		(0.1586)		(-0.0126)		(5.7471)
Priv. Targ. * Pmt. incl. Stock		-0.0309		-0.0305		0.0128
		(-0.7076)		(-0.6824)		(0.0303)
Sub. Targ. * All-Cash		0.0114		0.0220		-0.0852
		(0.2797)		(0.5406)		(-0.1781)
Pmt. Incl. stock	0.2824***		0.2800***		0.2629	
	(7.6975)		(7.3914)		(1.2676)	
Tender		-0.2439***				
		(-4.6479)				
Hostile	-0.1502	0.6021***	-0.5341	0.7007	0.1461	0.7081***
	(-0.7014)	(2.8977)	(-1.0797)	(1.3813)	(0.4991)	(3.1412)
ForeignTarg.	-0.2365***	0.0959	-0.2531***	0.0844	0.0203	0.2036*
	(-4.6643)	(1.5530)	(-4.7253)	(1.2375)	(0.1313)	(1.8454)
Multiple Bidders	0.1095	0.3859***	-0.1847	0.7092***	-0.0145	0.2047*
	(0.6952)	(2.9285)	(-0.8809)	(2.9414)	(-0.0894)	(1.8093)
Ln(Acq. Industry M&A)	-0.0182	-0.0401***	-0.0168	-0.0373**	0.0341	-0.0512*
	(-1.2653)	(-2.7497)	(-1.1009)	(-2.3447)	(0.7563)	(-1.9005)
Ln(Targ. Industry M&A)	-0.0028	-0.0241	-0.0087	-0.0285	0.0443	0.0306
	(-0.1829)	(-1.4679)	(-0.5167)	(-1.5806)	(0.9916)	(1.0093)
Lambda		-0.8655***		-0.9022***		0.7515***
		(-5.4614)		(-5.6022)		(6.9274)
Intercept	-0.6613**	-0.2209	-0.5097	-0.1382	-4.1287***	-1.3012
	(-1.9805)	(-0.6474)	(-1.3956)	(-0.3549)	(-4.0220)	(-1.5382)
N	5854	5854	5326	5326	528	528

Table 9

A Two-step Treatment Procedure for Advisory Fee

This table reports the estimation results of a two-step treatment procedure for the advisory fee paid by acquirers for public acquisitions in full sample as well as in the merger and tender subsamples. In eachmodel, the first column estimates the probit regression results of the first-stage selection equation, where the dependent variable is a dummy variable equal to 1 if a bidder hiresan industry specialist advisorand 0 otherwise. The results for the second-stage equation are shown in the second column for each model, where the dependent variable here is the natural logarithm of advisory fees paid by the bidder. The dummy variable 'Industry Specialist' is equal to 1 if the advisor is specializing in either the acquirer or the target industry or both; and 0 otherwise. The variable 'Lambda' is estimated from the first-stage equation and used as an additional regressor in the second-stage equation to adjust for self-selection bias. Other variables are defined in Appendix A. The z-statistics statistics in parentheses are adjusted for heteroskedasticity and bidder clustering. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. N denotes the number of observations.

	Full		Merger		Tender	
	(1)		(2)		(3)	
	Selection	Outcome	Selection	Outcome	Selection	Outcome
Industry Specialist		-0.9770***		-1.1931***		0.1620
		(-3.9561)		(-5.3557)		(0.3013)
Top 8		0.3904***		0.4585***		0.1969*
		(6.3450)		(6.2142)		(1.7562)
Ln(Deal Value)		0.6936***		0.6864***		0.6526***
		(30.7257)		(26.5035)		(11.9266)
Relatedness	0.1161	-0.0616	0.1248	-0.0529	0.0573	-0.0016
	(1.1092)	(-0.8233)	(0.9711)	(-0.5466)	(0.2526)	(-0.0194)
Pmt. Include Stock	0.3874***	0.0177	0.5959*	0.1808	0.0076	0.0848
	(3.1592)	(0.1146)	(1.9134)	(0.7787)	(0.0243)	(0.6593)
Relative Size	0.0968*	0.0162	0.0667	-0.0474	0.2258**	0.0371
	(1.6903)	(0.3447)	(0.8451)	(-0.6812)	(1.9959)	(1.1293)
Tender		0.3477**				
		(2.2569)				
Hostile	0.0649	-0.2550	-1.0576**	-0.4707	0.4628	-0.1000
	(0.2989)	(-1.3160)	(-2.2328)	(-1.1347)	(1.5261)	(-0.5386)
Foreign Target	0.0258	0.2887	0.0399	0.6946***	0.7381	-1.0462
	(0.0547)	(0.7845)	(0.0970)	(3.2885)	(1.2482)	(-1.3557)
Multiple Bidders	-0.0661	0.1251	-0.0015	0.2728	-0.1659	0.0366
	(-0.3924)	(1.0073)	(-0.0064)	(1.5433)	(-0.6436)	(0.2333)
Sigma	-9.8249**	9.6056***	-12.0724***	8.0652***	3.4413	8.1560
	(-2.4105)	(3.4179)	(-2.7021)	(2.5897)	(0.2198)	(1.4414)
Ln(Bidder Size)	-0.0148		-0.0540*		0.1802*	
	(-0.5411)		(-1.7161)		(1.7124)	
Tobin's Q	0.0058		0.0150		0.2691**	
	(0.2858)		(0.8151)		(1.9644)	

Run-up	0.1630*		0.2746***		-1.3743	
	(1.6609)		(2.8230)		(-1.4588)	
Free Cash Flow	-0.3899		-0.4274		-0.3045	
	(-1.0826)		(-1.2863)		(-0.1755)	
Leverage	0.1564		0.2097		0.3679	
	(0.5535)		(0.6676)		(0.3538)	
Ln(Acq. Industry M&A)	-0.0789**		-0.0732*		-0.0655	
	(-2.2980)		(-1.7785)		(-0.6666)	
Ln(Targ. Industry M&A)	-0.0010		-0.0308		0.1711**	
	(-0.0306)		(-0.7820)		(2.4294)	
Lambda		0.6049***		0.7468***		-0.0863
		(3.7949)		(5.2941)		(-0.2542)
Intercept	-1.0476	-13.5869***	-4.9135	-14.1152***	-5.3777**	-12.4612***
	(-1.2855)	(-25.0459)	(-0.0107)	(-27.6854)	(-2.4150)	(-11.0914)
N		888		680		208