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Do boutique investment banks have the Midas touch? Evidence from M&As

George Alexandridis[1] | Nikolaos Antypas[1] | Vicky Y. Lee[2]

[1]Henley Business School, ICMA Centre, University of Reading, Reading, UK

[2]Henley Business School, ICMA Centre, School of Accounting, Finance & Economics, University of Greenwich, London, UK

Correspondence
Vicky Y. Lee, Henley Business School, ICMA Centre, School of Accounting, Finance & Economics, University of Greenwich, Old Royal Naval College, Park Row, London SE10 9LS, UK.
Email: yl1629d@gre.ac.uk

Abstract

We study whether the meteoric rise of boutique advisors in mergers and acquisitions (M&As) is justified by their buy-side performance. We find that acquiring firms represented by boutique advisors generate superior short- and long-run abnormal returns over those employing full-service advisors. This effect is mainly prominent in private deals, interindustry mergers, and deals involving inexperienced acquirers, where valuation uncertainty tends to be higher. Overall, our results reflect that acquirer shareholders benefit from boutique investment banks' high level of industry expertise and independent advice, supporting the rising demand for their financial advisory services.

KEYWORDS

boutique advisors, mergers and acquisitions, value creation

JEL CLASSIFICATION

G24, G34

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1 | INTRODUCTION

By serving mid-size to large cap corporations, boutique investment banks have become a major driver of the financial advisory market in recent decades. Refinitiv (2019) reports that the merger and acquisition (M&A) fees earned by boutique investment banks surpassed those earned by top five banks in 2012.[1] In some cases, boutique advisor reputations, as manifested in various league tables, have climbed above those of bulge bracket banks, with boutique advisors now leading some of the largest M&A transactions and commanding an ever-growing share of the total deal value and revenue pie.[2] The success of boutique advisors can be attributed to a number of factors. Among them is the sector-specific knowledge and expertise that we tend to observe with boutique advisors. Further, most of the top-tier boutiques are typically founded by former bulge bracket dealmakers with access to established client and investor pipelines that are instrumental in handling large-scale transactions.[3] The very nature and structure of boutique financial advisors also tend to be associated with more independent advice and fewer conflicts of interest relative to full-service banks, which often arrange deal financing and cross-sell multiple financial services for profit (Allen et al., 2004; Song et al., 2013). Finally, negative investor perception and stricter regulatory scrutiny inflicted on large banks following the 2008 financial crisis catapulted demand for boutique M&A advisors.[4]

Despite the continuous growth of boutique advisors' market share, limited insights have been offered on the drivers of their success or whether this trend can be justified by their M&A dealmaking skills and ability to deliver synergistic value. The literature on financial advisors mainly focuses on examining the role of top-tier banks in driving M&A performance (Bao & Edmans, 2011; Golubov et al., 2012; Hunter & Jagtiani, 2003; Ismail, 2010; Rau, 2000; Servaes & Zenner, 1996). This is because, before the mid-2000s, the M&A advisory space was dominated by bulge bracket and other full-service financiers.

Furthermore, the only previous study on boutique advisors by Song et al. (2013) is limited to examining advisor quality through deal premia in public M&As. First, the majority of boutique deals involve private acquisitions, which comprise more than 60% of all deals in the M&A market. Much of the recent growth in boutique advisory, therefore, can be attributed to private deals. Hence, the question of whether boutiques are able to deliver value in a segment they specialize most remains largely unaddressed.[5] Second, while Song et al. show that acquiring firms hiring boutique advisors pay lower premia in public deals, prior studies report lower (higher) premia are associated with lower (higher) returns (Antoniou et al., 2008; Kisgen & Song, 2009). Thus, it cannot be surmised that boutique advisors also deliver superior returns for acquirers, and their economic contribution to shareholder value still needs to be examined. To address these significant gaps, our study aims to shed light on the overarching question of whether employing a boutique advisor comes with financial gains for acquiring firms and their shareholders.

We study a sample of US M&As with buy-side advisor data over the period 2000–2016. Our sample includes the post-2008 period to encapsulate the significant growth of boutiques in the

[1]See Refinitiv, 31 July 2018, 'Mega deals keep the M&A boom afloat'.
[2]League table rankings can be downloaded from the Refinitiv Mergers & Acquisitions database.
[3]See *The Financial Times*, 16 March 2014, 'Small proves beautiful at boutique banks'.
[4]See *The Financial Times*, 18 April 2019, 'Rise of the boutique banks'.
[5]Advising private deals requires different skill sets from advising public deals, largely because of information scarcity. Thus, boutique advisors' operation in specific regions and industries can be more useful in private acquisitions.

aftermath of the financial crisis.[6] Given the lack of advisor classification data, we manually identify and group financial advisors into boutiques and full-service banks. Overall, our sample comprises 1848 deals linked to boutique advisors and 3162 deals advised by full-service banks. In comparing advisory quality, we consider the actual value creation mechanism of boutique advisors by gauging their impact on short- and long-term abnormal returns. This approach allows us to capture a broader spectrum of potential gains that can be attributed to the dealmaking skills of boutique advisors. More importantly, it enables us to include private deals which have not been considered before.

Consistent with the rise in reputation and market share of boutique advisors, we find that the market reacts more favourably to deal announcements when the acquirer advisor is a boutique rather than a full-service bank. In particular, hiring a boutique advisor is associated with a 0.6% improvement in acquirer returns, which corresponds to a $72 million increase in shareholder value for the average-sized acquirer in our sample. In addition, boutique advisors appear to be more effective at creating value in private deals, where the difference in announcement returns reaches 1%. We also document that the effect of boutique advisors is persistent in the long run, as acquirers in boutique-led deals yield greater returns, ranging from 3.0% to 14.4% based on buy-and-hold and calendar-time strategies, than those in deals led by full-service advisors. In contrast, documented performance differentials are not observed in public deals.

These results from the ordinary least squares (OLS) estimates, however, should be interpreted with caution due to endogeneity concerns. First, since financial advisors are not randomly chosen by their clients, selection bias, whereby certain advisor selection criteria that are unaccounted for in our model, can be driving our results. This type of endogeneity can be corrected using Heckman's (1979) two-step procedure. Second, observable differences in acquirer and deal characteristics associated with both the advisor selection and deal outcome (confounders) can distort the causal relation and produce biased estimates. Observed confounding is particularly important to control for, given the presence of strong confounders in our sample, especially bidder size, and should be treated using a matching technique. Thus, we use propensity score matching (PSM) and compare advisor skills based on similar transaction portfolios. Overall, PSM results are more pronounced than the original OLS estimates: hiring a boutique advisor leads to an average 0.8% (1.2%) improvement in acquirer returns in all (private) deals, which translates into a $96 million ($104 million) increase in shareholder wealth.

To corroborate our findings, we investigate the sources of boutique advisors' value creation. Primarily, we focus on information scarcity or asymmetry associated with nonlisted firms (Capron & Shen, 2007; Officer et al., 2009). Similar to private deals, we find that boutique advisors outperform in deals characterized by greater information uncertainty, such as cross-industry mergers and deals involving acquirers without prior acquisition experience in the target industry. We also discover that most boutique advisors are industry specialists retaining more sector expertise than full-service banks. This explains why they are better at capitalizing on information asymmetry. To the contrary, full-service banks tend to be preferred for deal financing and for acquisitions financed entirely by cash. Finally, boutique advisors are less

[6]This period contains richer observations than the sample period (1995–2006) of Song et al. (2013) due to higher growth in boutiques' market share and revenue over the postcrisis period. For instance, Refinitiv, 7 May 2019, 'Boutique M&A Fees' highlights that boutique fees increased by 80% in 2018 compared with the precrisis peak in 2007. Moreover, several top-tier boutique investment banks in league tables—Centerview Partners, Moelis & Company, and PJT Partners—were only founded after 2006.

prone to conflicts of interest, since they engage in a smaller proportion of value-destroying deals and are more likely to withdraw from these deals.

Our study contributes to the literature in various important ways. We show for the first time that employing a boutique financial advisor can yield better returns for acquirers. Our findings challenge conventional belief that full-service banks are better at creating value in M&As due to their advanced capabilities and resources and offer a rational justification for the rise of boutique advisors' reputation and league table rankings. Second, we offer new evidence that boutique financial advisors outperform full-service banks—even the top-tier ones—when leading private deals, while they exhibit similar performance with more high-profile, public deals.[7] The fact that independent advisors facilitate superior M&A deal outcomes in acquisitions of private targets—as well as other types of transactions that are more prone to valuation uncertainty—adds to our understanding that they have a unique ability to mitigate information asymmetry. Lastly, our findings yield important economic implications associated with antitrust issues within the market for financial intermediation. Previously, the advisory space has been dominated by a small number of bulge bracket banks. This dominance of limited number of players can inhibit competition and a free market economy. The emergence of boutique firms, therefore, is meaningful in that it can promote healthy competition and potentially enhance the overall quality of advisory services.

The remainder of the paper is structured as follows. Section 2 describes the M&A data and advisor classification, discusses the market share of boutique advisors, and presents the sample descriptive statistics. Section 3 reports the key empirical results. Section 4 investigates the sources of value creation by boutique advisors. Section 5 examines the link between financing needs and advisor choice. Section 6 presents the results from additional robustness tests, and Section 7 concludes the study.

2 | SAMPLE AND DESCRIPTIVE STATISTICS

2.1 | Data collection

M&A transactions data are from the Refinitiv SDC Platinum Mergers & Acquisitions Database and meet the following criteria. The sample includes M&As announced between 1 January 2000, and 31 December 2016, where both the target and the acquirer are US firms. Acquirers are public and targets are either public or private companies. We exclude transactions involving repurchases, recapitalizations, self-tenders, exchange offers, acquisitions of remaining interest, minority stake purchases, and intra-corporate restructurings. Acquirers are required to own less than 10% of the target firm's shares before the announcement and seek to acquire more than 50% after completion. Both completed and withdrawn deals with a transaction value of at least $1 million are included. We also require that acquirers have nonmissing data on their buy-side financial advisor(s). Imposing these conditions yields 5010 M&A deal observations. We collect accounting and stock price data from Compustat and the CRSP, respectively, with share codes 10 and 11. For our main tests, we exclude 934 deals where both boutique and full-service advisors are involved. Given the

[7]Golubov et al. (2012) find that top-tier advisors generate higher abnormal returns in public deals, arguably, because they devote more resources and effort to these deals than to smaller private deals to preserve their reputational capital. Using a more recent sample period though, we find that the observed performance of top-tier versus boutique advisor changes over the post-2000 period. See the performance of boutique advisors over different sample periods in Section 6.6.

lack of information on the role each advisor plays in the process of an M&A that involves multiple advisors, including these transactions could generate bias in our results.

2.2 | Advisor classification

Classifying financial advisors entails challenges, given the inherent complexities in identifying a boutique investment bank in the absence of a commercially available database. While Song et al. (2013) define boutique advisors as those who offer M&A advisory services only, this can be too strict for today's standards and potentially result in misclassifying some boutique advisors as full-service banks. More recently, boutique investment banks started offering services beyond M&A advisory, with various divisions acting independently from each other.[8] Therefore, we apply a less strict classification standard to define boutique investment banks.

We manually classify boutique advisors using a dual classification approach to improve accuracy. First, we search whether an individual investment bank is explicitly referred to as boutique in sources such as company websites, news media, S&P Global Market Intelligence accessed through Bloomberg's private company information section, US Securities and Exchange Commission filings, and past/local periodicals around the time of deal announcements. Second, we take into account parameters such as a bank's focus on M&A advisory service, active regions, sectors of specialism, and average asset value of corporate clients. These parameters are determined after analysing typical characteristics of M&A advisors defined as advisory boutique by the industry.

Boutique investment banks typically serve small to middle-market firms with a mean asset value of $50 million to $500 million, although some boutiques also serve large-cap clients. Their services are independent, and most boutiques focus on advising M&A transactions within specific regions and industries, along with general corporate finance advisory services such as divestitures, valuations, and restructurings. Despite the fact that some boutique advisors also offer additional services, such as wealth management, private placement, and research, this should not automatically disqualify them from being classified as 'boutique', as long as corporate finance advisory is their core business and these products are largely independent. These additional screenings ensure our classification satisfies the characteristics of typical boutique advisors. To the contrary, a financial advisor providing both commercial and investment banking, where M&A advisory is just part of their largely diversified operations, would be classified as a full-service advisor.

The following are excerpts for Bigelow LLC, which is classified as a boutique advisor based on our dual classification approach:

> Bigelow LLC is an independently owned mergers & acquisitions advisory boutique focused on entrepreneur Owner-Managers. (Bigelow website)[9]

> The Bigelow Company LLC is an investment banking firm that provides financial advisory services to middle-market entrepreneurial companies in North America. It focuses on transactions between $25 million to $300 million. The firm provides restructuring, recapitalization, mergers and acquisition, divestiture, management consulting, debt and

[8] See Thomson Reuters, 14 December 2016, 'As good as it gets? Boutique banks look to grow beyond M&A'. We thank Lei Zhou and colleagues for sharing their list of financial advisors.

[9] See https://bigelowllc.com.

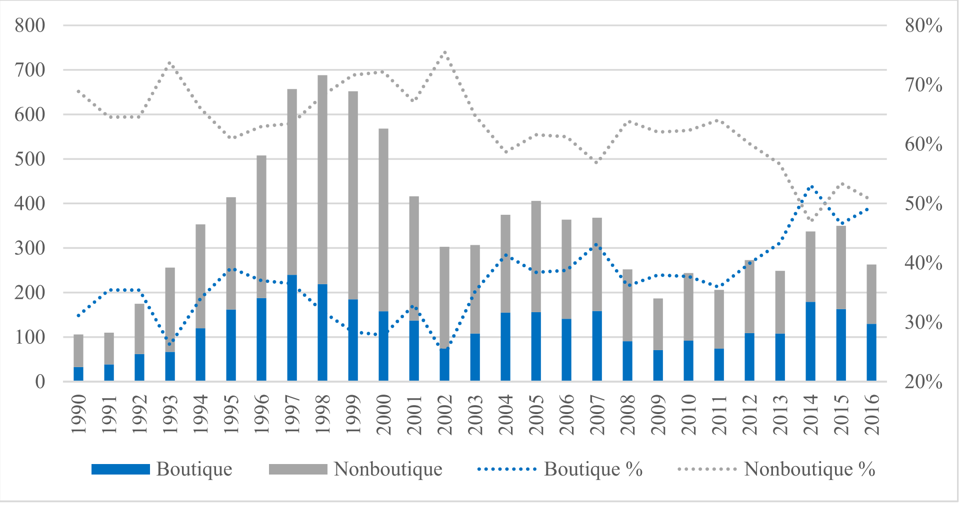

FIGURE 1 Buy-side advisor market share by the number of deals: Boutique versus nonboutique. This figure presents market share of buy-side boutique versus nonboutique advisors for a sample of US mergers and acquisitions announced over the period 1990–2016 based on the number of deals. [Color figure can be viewed at wileyonlinelibrary.com]

> equity financing, and valuation advisory services. It focuses on aerospace, manufacturing, automotive, building materials, business services, commercial printing, computer hardware, distribution, education, electronics, environmental, industrial tools, metals, materials, publishing, specialty food, software, and telecommunications industries. (S&P Global Market Intelligence)[10]

The first source describes Bigelow as an M&A advisory boutique. The second source highlights the characteristics of a typical boutique advisor, specifically, the average size of its corporate clients, types of services provided, and specific sectors of expertise. Following this comprehensive classification approach, we identify 243 boutique advisors and 74 full-service banks between 2000 and 2016.[11] However, since we exclude 934 mixed advisor deals from our main analysis, our final sample comprises 212 boutique and 71 full-service advisors.

2.3 | Market share of boutique financial advisors

In this section, we examine how the market share of boutique advisors has evolved over time. Figures 1 and 2 show the change in the market share of boutique versus nonboutique advisors by the number of deals and deal value, respectively.[12] Both figures show that the market share of boutiques has discernibly increased over time, especially after the 2008 financial crisis.

At least three factors can explain this trend. First is the role of regulation. The late 1990s were marked by a wave of M&A mega-deals consummated by full-service banks, especially

[10]See 'Company Overview of The Bigelow Company LLC' provided by S&P Global Market Intelligence.
[11]Our advisor classification data is available upon request.
[12]The trendline in Figure 2 is smoothed using moving average to present a clearer pattern.

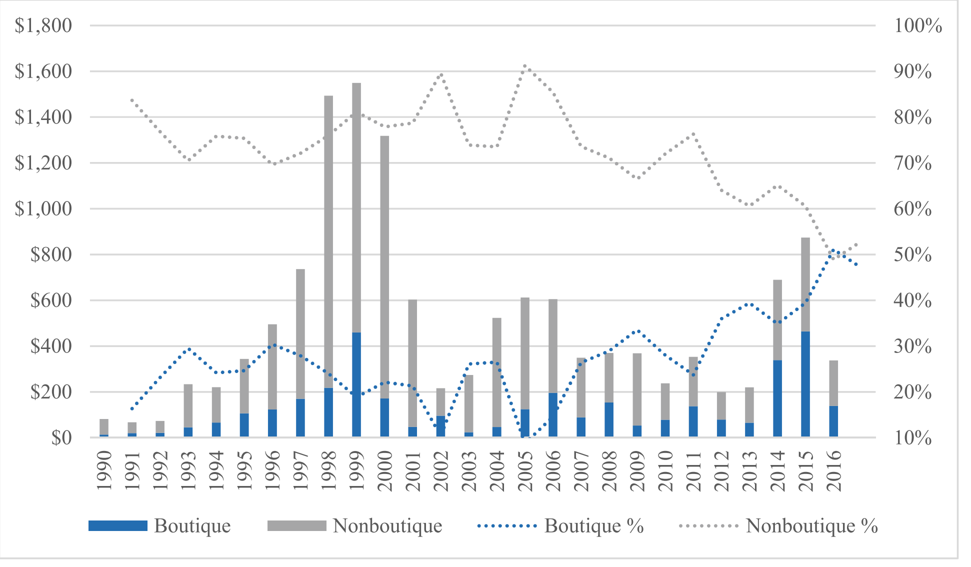

FIGURE 2 Buy-side advisor market share by deal value (in billions of US dollars): Boutique versus nonboutique. This figure presents market share of buy-side boutique versus nonboutique advisors for a sample of US mergers and acquisitions announced over the period 1990–2016 based on deal value. [Color figure can be viewed at wileyonlinelibrary.com]

bulge brackets. This trend was underpinned by Section 20 Subsidiaries of Bank Holding Companies, enacted in 1997, which effectively allowed commercial banks to increase their investment banking activities mostly through acquisitions. This blurred the line of separation between commercial and investment banks (Bhargava & Fraser, 1998; Cornett et al., 2002). Further, in 1999, the repeal of the Glass–Steagall Act (Gramm–Leach–Bliley Act) spurred more merger activities by full-service and bulge bracket banks, up until 2007, before the financial crisis (Crawford, 2011; Cyree, 2000). During this period, large full-service banks benefited from larger deals due to their financing capacity and resources. Since 2007, however, bulge bracket banks faced regulatory hurdles, as well as negative investor perception. Subsequently, the Dodd–Frank Act, enacted in 2010, forced full-service banks to revert to a more traditional business model by separating their commercial banking from investment banking operations (Balasubramnian & Cyree, 2014). The regulatory framework was more lenient towards independent investment banks, allowing them to reinvent and repurpose themselves. As a result, boutique investment banks' market share in the advisory space soared.

Second, in the most recent merger wave, multibillion-dollar mega-deals became less prevalent relative to the waves of the 1990s and 2000s, which allowed smaller business combinations to thrive, providing a fruitful building block for boutique advisors to grow their market share. In addition, financing capability, one of full-service banks' key competitive advantages, became less important within an environment of low interest rates, growing corporate cash reserves, and stock-for-stock transactions being more widely accepted and utilized as a financing method for acquisitions.[13]

[13]See Deloitte, 31 July 2018, 'Battle for dominance in the M&A advisory business—Bulge-brackets vs. the boutiques'.

The distinct qualities and skills that boutique banks bring to the market have also become vital drivers of their increasing market share. Due to the independent nature of their advice, boutiques are less prone to conflicts of interest. In addition, many of them are founded by reputable bankers formerly employed by bulge bracket banks and have established track records and business relationships with major corporate clients. Boutique advisors often service clients in specific sectors (e.g., technology, retail, financial services, and healthcare) or niche markets (e.g., small to medium-sized mergers, business valuations, and fairness opinion), where demand for independent financial advice has grown more recently.

While the above factors are believed to have collectively contributed to the increase in market share of boutique advisors, we focus on investigating whether their track record of attaining favourable deal outcomes has further strengthened their position in the advisory market.

2.4 | Descriptive summary statistics

Table 1 reports summary statistics for all sample, as well as the boutique and full-service advisor subsets, respectively. The variable definitions are provided in Appendix A. The variable *bidder size* seems to have a significant impact on advisor choice, with boutique investment banks normally advising significantly smaller companies ($6.5 billion) than full-service banks ($15.2 billion) do. Accordingly, *deal value* is also significantly smaller for boutique advisors ($724.5 million) than for their full-service counterparts ($2.1 billion). The difference in *relative size* (Asquith et al., 1983; Fuller et al., 2002) between the two groups seems negligible. The book-to-market ratio, *book-to-market* (Lang et al., 1989; Martin, 1996; Rau & Vermaelen, 1998), of acquirers advised by boutiques (0.551) is higher than for those employing full-service banks (0.463). The variable *leverage* can be linked to financing needs and, thus, to advisor choice. The mean leverage ratio of acquirers hiring full-service (boutique) advisors is 0.226 (0.157), suggesting that acquirers with higher leverage and potentially in need of a financing arrangement are more likely to involve full-service banks.

Public deals and private deals comprise 39.9% and 60.1% of our sample, respectively. Boutique investment banks provide a greater proportion of M&A advice in *private deals* (62.2%) than full-service banks (58.9%) do, with around 38% of their focus still being given to *public deals*. Boutique advisors are also more likely to advise on *stock deals,* since 73.9% (65.4%) of their (full-service) deals involve a full or partial stock swap.

Further, while approximately 34% of the transactions in our sample are *diversifying deals*, full-service banks advise a slightly higher (35.2%) proportion of these deals than boutique banks (31.7%) do. *Hostile deals* (Bhagat et al., 1990; Malmendier et al., 2016) comprise only 1.6% of total acquisitions in our sample, more of which are advised by full-service banks. *Tender offers* (Dodd & Ruback, 1977; Jarrell & Poulsen, 1989; Lang et al., 1989) represent 5.6% of our sample, and a relatively larger share of these deals are advised by full-service banks.

The mean difference test results in the last column of Table 1 show that the characteristics of acquirers and deals managed by the two advisor groups are significantly different, except for the variables *run-up* (Keown & Pinkerton, 1981; Masulis et al., 2007), *volatility* (Moeller et al., 2007), and *relative size*. Our empirical analysis should therefore account for these observed confounders that could be driving M&A outcome.

TABLE 1 Descriptive summary statistics.

This table presents summary statistics for a sample of US mergers and acquisitions (M&As) announced between 1 January 2000, and 31 December 2016, which involve a buy-side financial advisor. The number of observations, denoted as *N*, and the mean and median are provided for (1) all sample, as well as the (2) boutique and (3) full-service subsets. The variable definitions are available in Appendix A. The variables *bidder size* and *deal value* are in millions of US dollars and adjusted for inflation. The last column presents the mean difference between the (2) boutique and (3) full-service subsets for each variable. The significance of the mean difference is estimated using *t*-tests. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. M&A transaction data are obtained from the Refinitiv SDC Platinum Mergers & Acquisitions Database. Acquiring firms' stock price and accounting data are collected from the CRSP and Compustat, respectively.

	All sample (1)			Boutique (2)			Full-service (3)			Mean difference
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median	(2) – (3)
Bidder size	4991	12,004.420	1478.700	1844	6480.808	556.808	3147	15,241.007	2701.047	−8760.199***
Book-to-market	4431	0.495	0.425	1601	0.551	0.501	2830	0.463	0.386	0.087***
Run-up	4778	−0.014	−0.000	1792	−0.006	−0.003	2986	−0.019	0.002	0.013
Volatility	4778	0.027	0.021	1792	0.027	0.020	2986	0.026	0.021	0.001
Leverage	4445	0.201	0.162	1602	0.157	0.109	2843	0.226	0.197	−0.069***
Deal value	5010	1609.302	255.130	1848	724.484	95.128	3162	2126.425	430.395	−1401.941***
Relative size	4991	0.436	0.180	1844	0.407	0.179	3147	0.452	0.181	−0.045
Public deals	5010	0.399	-	1848	0.378	-	3162	0.411	-	−0.034*
Private deals	5010	0.601	-	1848	0.622	-	3162	0.589	-	0.034*
Diversifying deals	5010	0.339	-	1848	0.317	-	3162	0.352	-	−0.035*
Hostile deals	5010	0.016	-	1848	0.011	-	3162	0.020	-	−0.009*
Tender offers	5010	0.056	-	1848	0.032	-	3162	0.071	-	−0.039***
All cash	5010	0.314	-	1848	0.260	-	3162	0.346	-	−0.086***
All stock	5010	0.182	-	1848	0.207	-	3162	0.168	-	0.040***
Mixed payments	5010	0.503	-	1848	0.532	-	3162	0.486	-	0.046**
Premium	1847	49.127	38.312	615	50.807	39.651	1232	48.289	37.636	2.519
CAR	4936	0.005	0.001	1828	0.008	0.002	3108	0.004	0.001	0.004

3 | EMPIRICAL ANALYSIS

3.1 | OLS regression analysis for bidder CARs

In examining the role of boutique advisors in M&A performance, we use the 3-day (−1, +1) cumulative abnormal returns (CARs) surrounding the deal announcement date in multivariate cross-sectional OLS regression analysis[14] (Bowers & Miller, 1990; Golubov et al., 2012; Kale et al., 2003; Walter et al., 2008). Throughout all regressions, our main variable of interest is *boutique*, a dummy that takes the value of 1 if the deal involves a boutique advisor, and 0 otherwise. We include a set of control variables that are known to affect acquirer returns. The variable *bidder size* normally has strong negative effects on bidder returns (Moeller et al., 2004; Song et al., 2013). Other important control variables include *book-to-market*, which accounts for the effect of growth versus value firms; *run-up*, a measure of preannouncement stock price movement; and *public deals*, *tender offers* and *leverage*. The rest are a measure of deal/valuation complexity such as acquirer stock price *volatility*, *relative size*, *stock deals*, *diversifying deals* and *hostile takeovers*. See Appendix A for the definitions of these variables. We also control for year fixed effects and industry fixed effects using Fama and French's 12-industry classification method. All continuous variables are winsorized at 1%, and standard errors are adjusted for heteroscedasticity and bidder clustering.

Table 2 presents the results for the full sample in column (1), as well as the subsets of public deals in column (2) and private deals in column (3). The boutique coefficient in column (1) is positive and statistically significant (at the 10% level), indicating that acquirers employing boutique investment banks generate, on average, 0.6% higher returns than those employing full-service advisors. This excess return is equivalent to a $72 million upside for an average-sized acquirer.[15] While the return differential in public deals is insignificant, boutique advisors are associated with a 1.0% higher CAR (at the 5% level) in private deals, which is equivalent to a $86.7 million in shareholder wealth gain.[16] Our results point to economically and statistically superior acquirer returns in private deals when the advisor is a boutique bank.

In untabulated analysis, we confirm that the documented outperformance of boutiques persists when we restrict the sample of full-service counterparts to a top-tier bulge bracket subset (we categorize full-service banks into the top five, eight, or ten advisors, based on the deal value). This finding is different from that of Golubov et al. (2012), which studies an earlier period, and suggests that the performance of boutiques could have improved more recently. We explore this possibility further in Section 6 as part of additional robustness tests.

3.2 | Sample selection bias and observed confounding

Our analysis based on the OLS regression framework suggests that boutique advisors contribute positively to acquirer shareholder returns. However, this methodology could produce

[14]Most event studies use CARs as a proxy for the value creation of acquirer shareholders in M&As instead of deal premia, which predicts neither the success of a merger nor its effect on shareholder wealth. See Renneboog and Vansteenkiste (2019) for a review of M&A event studies. Campa and Hernando (2004) and Martynova and Renneboog (2011) also argue that CARs effectively capture expected takeover synergies.

[15]The mean dollar gain is computed as the average market value of acquirers ($12 billion) in our sample multiplied by the boutique coefficient (0.6%) in model (1).

[16]The mean dollar gain in private acquisitions is estimated as the average market value of bidders ($8671.23 million) acquiring private targets multiplied by the boutique coefficient (1.0%) in model (3).

precarious inferences, because the OLS estimator is susceptible to sample selection bias (Heckman, 1979; Roy, 1951), a type of endogeneity caused by the nonrandom selection of the treatment variable. Specifically, the coefficient for *boutique* estimated in Table 2 could misrepresent its impact on acquisition performance if advisors are selected nonrandomly based on unobservable factors that are not accounted for in the model. In this case, the analysis would suffer from causal inference (Heckman, 1989), which refers to our inability to observe a counterfactual outcome had a firm hired a boutique advisor for a full-service deal, and vice versa. Another issue is that, as we observe in our summary statistics, our regression model contains strong confounders that can affect both advisor choice and deal outcome, with the strongest confounder being the bidder size variable. Rosenbaum and Rubin (1983) suggest that a direct comparison between the treatment and control groups can be misleading in nonrandomized experiments, since the distribution of their characteristics can differ systematically. Regardless, prior studies investigating the quality of M&A advisors do not account for heterogeneity in their client portfolios and simply compare overall deals among different groups of advisors. It should be emphasized that such a direct comparison of different advisor groups may yield unreliable performance estimates.

We employ two methodologies to tackle these issues. First, we use Heckman's inverse Mills ratio (*IMR*) to account for selection bias caused by unobservable factors, that is, omitted variable bias. We also implement PSM to treat observed confounding factors and produce counterfactual outcomes. Both methods involve a two-stage analysis, where in the first stage we estimate the advisor selection between boutique and full-service banks based on factors that influence the decision. The second stage is different for each method. The Heckman procedure entails the inclusion of *IMR*, a selection bias correction term that is generated in the first-stage regression. If the coefficient of the IMR proves insignificant, we can infer that our OLS estimates are not affected by the selection bias. In the PSM process, we match deals from the treatment group, that is, boutique deals, with those from the control group, that is, full-service deals, based on the similarity of confounders (acquirer or deal characteristics). Then, we estimate the differences in mean bidder CARs between the treatment and counterfactual outcomes using matched observations only. The results of these methods are discussed in the next two sections.

3.3 | Heckman's two-step analysis

The following equation is the first-stage model estimated by probit regression, where the dependent variable takes the value of 1 if the advisor is a boutique, and 0 otherwise:

$$\begin{aligned} &\Pr(choice\ \ of\ \ boutique\ \ advisor_{i,t} = 1) \\ &\quad = \Phi[\alpha + \beta\, industry\ \ peers_{i,t} + \gamma\, control\ \ variables_{i,t} + \varepsilon_{i,t}], \end{aligned} \tag{1}$$

We also include an instrumental variable, *industry peers*, which should influence the advisor selection but not the announcement returns. This variable, inspired by Graham et al. (2017), captures whether an acquirer's selection of a boutique advisor is affected by that of its industry peers. It is measured as the number of boutique advisors hired by an acquirer's industry peers—based on the same three-digit SIC code—over the year before the announcement, divided by the total number of advisors employed by the same group of peers

TABLE 2 Multinomial cross-sectional ordinary least squares (OLS) regression analysis: Bidder CARs.

This table presents results from the cross-sectional OLS regression analysis for a sample of US mergers and acquisitions announced over the period 2000–2016. The bidders are public firms, while the targets are public or private firms. The dependent variable is the 3-day bidder CAR (−1, +1) surrounding the announcement date. The variable boutique is a dummy equal to 1 if the deal is advised by a boutique investment bank, and 0 otherwise. The bidder size variable is the logarithm of the bidder market value 4 weeks before the announcement. The control variables are selected based on firm and deal characteristics and are defined in Appendix A. Specifications (1)–(3) include all deals and the public and private subsets, respectively. The regressions control for year and industry fixed effects. All control variables are winsorized at 1%, and standard errors are adjusted for heteroscedasticity and bidder clustering. The *p* values are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	All	Public	Private
	(1)	(2)	(3)
Boutique	0.006*	0.000	0.010**
	(0.082)	(0.990)	(0.014)
Bidder size	−0.002	−0.005***	0.002
	(0.143)	(0.002)	(0.253)
Book-to-market	−0.018***	−0.021**	−0.017**
	(0.003)	(0.045)	(0.017)
Run-up	0.020**	0.021	0.022*
	(0.035)	(0.193)	(0.058)
Volatility	0.136	-0.080	0.215
	(0.452)	(0.798)	(0.338)
Public deals	−0.033***		
	(0.000)		
Stock deals	−0.013***	−0.026***	−0.004
	(0.000)	(0.000)	(0.310)
Relative size	0.003**	−0.007***	0.012***
	(0.015)	(0.000)	(0.000)
Diversifying deals	−0.005*	−0.005	−0.007*
	(0.084)	(0.273)	(0.078)
Tender offers	0.010*	−0.003	
	(0.053)	(0.591)	
Hostile deals	0.009	0.017*	
	(0.317)	(0.090)	
Leverage	0.034***	0.039**	0.030***
	(0.000)	(0.012)	(0.004)
Constant	0.039**	0.032	0.034
	(0.013)	(0.214)	(0.112)

TABLE 2 (Continued)

	All	Public	Private
	(1)	(2)	(3)
Observations	3924	1552	2372
Adjusted R^2	0.061	0.081	0.037
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

over the same period. This instrumental variable is created based on the notion that acquirers in the same industry share views and experiences regarding the value of a financial advisor through their information network. Hence, industry peers are expected to have an impact on the choice of a boutique advisor.

In the selection stage, we use the same set of control variables as in our previous regression, excluding the *tender offers* variable, which is irrelevant to the choice of advisor. Interestingly, the first-stage regression in Table 3 indicates that an acquirer's decision to hire a boutique advisor is significantly associated with that of its industry peers (at the 1% level in all specifications), implying the effect of information sharing on M&A advisors. We also find that the probability of hiring a boutique advisor increases when the target is *public* and when the transaction involves *stock offers* in the regressions of all and private deals. Stock offers are typically more difficult to negotiate than cash offers and are known to have a negative effect on announcement returns due to the potential implication of bidder overvaluation (S. Chang, 1998; Martynova & Renneboog, 2011). Thus, the preference for boutique advisors in these deals suggests that they could have knowledges and skills valuable for complex deals. To the contrary, *bidder size*, *relative size*, and *leverage* are negatively related to the choice of boutique advisors, implying that the transaction scale and financing requirement can be a focal issue when hiring a boutique advisor. The *book-to-market* ratio and price *volatility* are also negatively associated with the choice of boutique advisors.

In the second-stage model estimated by the OLS regression, we include the *IMR,* obtained from the advisor selection equation, to examine whether unobservable bias drives deal outcomes:

$$bidder\ \ CAR_{i,t} = \alpha + \gamma\, control\ \ variables_{i,t} + IMR_{i,t} + \varepsilon_{i,t}, \tag{2}$$

If our results are affected by the omitted variable bias, the *IMR* coefficient would be statistically significant. The *IMR* coefficient is significant in all deals (at the 5% level), but insignificant in the regressions for public and private subsamples. The positive and significant coefficient suggests the existence of positive selection bias, where an unobservable factor that increases the probability of hiring boutique advisors also produces upwardly biased estimates on acquirer performance. The coefficient of *boutique* in the second-stage regression reflects an estimate after correcting for selection bias. Overall, our results are consistent with the initial findings and corroborate that hiring boutique advisors have a significantly positive effect on acquirer deal outcomes, a result that seems to be driven by private deals.

TABLE 3 Heckman's two-step (inverse Mills ratio) analysis: Advisor selection and bidder CAR.

This table presents Heckman's two-step analysis for a sample of US mergers and acquisitions announced over the period 2000–2016. While all bidders are public firms, the sample is split into all deals and public or private subsets, depending on the target firms' public status. For each specification, the results of two regression analyses are reported: (1) the selection model is estimated by probit regression analysis, where the dependent variable is a dummy equal to 1 if the deal is advised by a boutique investment bank, and 0 otherwise; (2) the outcome model measures acquirer performance using cross-sectional ordinary least squares regression analysis, where the dependent variable is the 3-day bidder CAR (−1, +1) surrounding the announcement date. In the selection stage, we include an instrumental variable, *industry peers*, which indicates the average use of boutique advisors by the acquiring firm's industry peers; it is computed as the number of boutique advisors hired by a bidder's industry peers (based on the same three-digit SIC code) over the past year before the announcement date, divided by the total number of advisors employed by the same group of peers over the same period. The IMR value generated in the selection stage is added to the second-stage regression to control for (unobservable) selection bias. The definitions of the control variables are available in Appendix A. The regressions control for year and industry fixed effects. All control variables are winsorized at 1%. The *p* values are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	All		**Public**		**Private**	
	Selection	**Outcome**	**Selection**	**Outcome**	**Selection**	**Outcome**
Boutique		0.006*		−0.000		0.010**
		(0.084)		(0.978)		(0.014)
Industry peers	0.510***		0.665***		0.408***	
	(0.000)		(0.001)		(0.001)	
Bidder size	−0.473***	−0.009**	−0.451***	-0.012**	−0.482***	−0.006
	(0.000)	(0.016)	(0.000)	(0.013)	(0.000)	(0.278)
Book-to-market	−0.325***	−0.023***	−0.472***	−0.028**	−0.236**	−0.021***
	(0.000)	(0.001)	(0.002)	(0.018)	(0.018)	(0.008)
Run-up	−0.003	0.020**	-0.405**	0.015	0.167	0.025**
	(0.977)	(0.035)	(0.045)	(0.367)	(0.195)	(0.032)
Volatility	−5.577**	0.048	−3.706	−0.127	−5.102*	0.129
	(0.018)	(0.789)	(0.321)	(0.682)	(0.081)	(0.570)
Public deals	0.143**	−0.031***				
	(0.012)	(0.000)				
Stock deals	0.108**	−0.011***	−0.013	−0.026***	0.136**	−0.002
	(0.050)	(0.000)	(0.896)	(0.000)	(0.040)	(0.665)
Relative size	−0.351***	−0.002	−0.337***	−0.012***	−0.358***	0.006
	(0.000)	(0.478)	(0.000)	(0.001)	(0.000)	(0.198)
Diversifying deals	0.046	−0.005	0.086	−0.004	0.051	−0.006
	(0.400)	(0.129)	(0.393)	(0.371)	(0.422)	(0.129)
Tender offers		0.010**		−0.002		
		(0.050)		(0.696)		

TABLE 3 (Continued)

	All		Public		Private	
	Selection	Outcome	Selection	Outcome	Selection	Outcome
Hostile deals	−0.008	0.008	0.149	0.018*		
	(0.971)	(0.388)	(0.499)	(0.061)		
Leverage	−0.685***	0.023**	−0.691**	0.029*	−0.701***	0.018
	(0.000)	(0.024)	(0.016)	(0.077)	(0.000)	(0.184)
IMR		0.022**		0.019		0.024
		(0.047)		(0.165)		(0.157)
Constant	2.697***	0.063***	2.995***	0.058*	2.585***	0.057**
	(0.000)	(0.001)	(0.000)	(0.054)	(0.000)	(0.030)
Observations	3924	3924	1552	1552	2372	2372
Pseudo-R^2 (adj. R^2)	0.260	0.062	0.342	0.081	0.225	0.037
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

3.4 | PSM

The summary statistics in Table 1 exhibit significant differences in acquirer and deal characteristics between the boutique and full-service groups. Such intergroup heterogeneity can confound estimates by affecting both the advisor selection and acquirer performance. To control for the confounding effect, we employ PSM (Caliendo & Kopeinig, 2008; Dehejia & Wahba, 2002).

First, we estimate an advisor selection model via logit regression with a set of bidder and deal characteristics and obtain the propensity scores (the probability of receiving treatment) for each deal.[17] Subsequently, we match deals in the treatment group (boutique advisors) with deals in the control group (full-service advisors) based on similar propensity scores. In this stage, a range of matching techniques (nearest neighbour matching and Gaussian kernel matching)[18] are employed to validate the consistency of our results. Finally, we use the average treatment effect on the treated (ATT) to obtain the mean difference in bidder CARs between the treated, $Y_i(1)$, and the control group, $Y_i(0)$, as follows:

$$\text{ATT}= E(\Delta | d = 1) = E(Y(1) | d = 1) - E(Y(0) | d = 1), \tag{3}$$

where $Y_i(1)$ is the observed outcome (boutique CARs) and $Y_i(0)$ is the counterfactual outcome, which is unobservable and should be estimated using the outcome of matched full-service deals (full-service CARs).

[17]The probability of receiving treatment in our model is the probability of a boutique advisor being selected by an acquirer.

[18]For nearest neighbour matching, we use one-to-one and one-to-five matching in which a deal from the treatment group is matched with either the closest deal or the five closest deals, respectively, in the control group, based on the similarity of propensity scores. Gaussian kernel matching uses all deals in the control group within a certain bandwidth while giving a larger weight to deals with closer proximity to a matching deal in the treatment group.

Panel A of Table 4 presents results from the logit regression analysis on the choice of boutique advisors, and Panel B summarizes the treatment effects on bidder CARs.[19] In general, boutique advisors are associated with a significant improvement in acquirer CARs, and these posttreatment returns are greater than the OLS estimates. According to one-to-one nearest neighbour matching, acquirers experience an average of 1% higher returns, or $120 million in dollar gains, when hiring a boutique advisor. Similar to our initial findings, acquirer CARs exhibit little difference between boutique and full-service advisors in public deals. In private deals, however, boutique advisors seem to enhance acquirer returns significantly by an average of 1.2%,[20] which translates into $104 million in additional wealth gains.

3.5 | Long-run abnormal returns

Since our short-run event window returns reflect market expectations rather than actual deal outcomes, which may take longer to materialize, we further examine whether boutique advisors can also add value in the longer term. To that end, we estimate buy-and-hold abnormal returns (BHARs) and calendar-time portfolio regressions (CTPRs). BHARs are calculated using an acquirer's compounded returns adjusted by those of a benchmark portfolio:

$$BHAR_i = \prod_{t=1}^{T}[1 + R_{i,t}] - \prod_{t=1}^{T}[1 + R_{benchmark,t}], \tag{4}$$

where $R_{i,t}$ is the monthly returns of sample firm i, compounded over the 12- and 24-month period beginning with the announcement date, and $R_{benchmark,t}$ is returns of a benchmark portfolio compounded over the same period.

To obtain benchmark returns, we use the control firm approach of Barber and Lyon (1997), where a benchmark is selected based on a similar size and book-to-market ratio to the sample firm's.[21] Barber and Lyon assert the importance of controlling for these factors, since they are significantly related to common stock returns. To construct a benchmark portfolio, all firms listed on the New York Stock Exchange are allocated into five size and book-to-market quintiles. Then, a 5×5 matrix (combination of five size categories and five book-to-market categories) is formed to create 25 size/book-to-market portfolios.

Due to delisting, not all sample firms have valid return data over the full estimation period. In such cases, we replace any missing monthly returns of the sample firms with their delisting returns and, if these are not available, with returns of the corresponding benchmark portfolio. Further, in cases where an acquirer completes multiple acquisitions within our 1- or 2-year event window, we only include the initial deal and ignore additional acquisitions followed afterwards. Table 5 presents the results from a multivariate OLS model based on equally weighted BHARs. Consistent with our results for announcement returns, shareholders of acquiring firms hiring boutique advisors earn overall higher returns in the long term, with an

[19]See Appendix B for how many deals are matched based on PSM.

[20]This is the average of all three matching outcomes in private deals.

[21]We have opted for the control firm approach since it is shown to account for new listing bias (market indices often include newly listed firms with stock prices available sometime after the event month), portfolio rebalancing bias (indices are frequently rebalanced with the inclusion of new stocks and the exclusion of existing stocks), and positive skewness bias and tends to yield well-specified test statistics (Barber & Lyon, 1997; Fama & French, 1992, 1993; Mitchell & Stafford, 2000). It is also important to note that in our tests the benchmark portfolio is not rebalanced to match the event portfolio.

TABLE 4 Propensity score matching (PSM): Boutique versus full-service.

This table exhibits the results from the PSM on boutique versus full-service deals for a sample of US mergers and acquisitions announced over the period 2000–2016. While all bidders are public firms, the sample is split into all deals and public or private subsets, depending on the target firms' public status. The PSM procedure is as follows. First, boutique deals are matched with full-service deals based on the similarity of their propensity scores, calculated using acquirer and deal characteristics in logit regression analysis, as in Panel A. The dependent variable in Panel A is a dummy equal to 1 if the deal is advised by a boutique investment bank, and 0 otherwise. Second, the mean difference in bidder CARs between the treatment group, that is, boutique deals, and the control group, that is, full-service deals, is estimated based only on these matched deals using the ATT, as in Equation (3). These returns are presented in Panel B based on different matching methods: one-to-one nearest neighbour matching, five-nearest neighbour matching, and Gaussian kernel matching. The definitions of the control variables are available in Appendix A. All control variables are winsorized at 1%. The regressions control for year and industry fixed effects. The *p* values are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Logit regression: Choice of boutique advisor			
	All	**Public**	**Private**
Bidder size	−0.852***	−0.846***	−0.843***
	(0.000)	(0.000)	(0.000)
Book-to-market	−0.567***	−0.827***	−0.409**
	(0.000)	(0.002)	(0.015)
Run-up	0.019	−0.712**	0.305
	(0.917)	(0.049)	(0.163)
Volatility	−10.768***	−8.494	−9.375*
	(0.008)	(0.200)	(0.059)
Public Deals	0.265***		
	(0.006)		
Stock deals	0.209**	0.060	0.226**
	(0.026)	(0.734)	(0.044)
Relative size	−0.620***	−0.616***	−0.620***
	(0.000)	(0.000)	(0.000)
Diversifying deals	0.067	0.135	0.082
	(0.469)	(0.437)	(0.453)
Hostile deals	0.068	0.400	
	(0.857)	(0.314)	
Leverage	−1.202***	−1.217**	−1.233***
	(0.000)	(0.014)	(0.000)
Constant	4.776***	5.422***	4.493***
	(0.000)	(0.000)	(0.000)
Observations	3924	1552	2372

(Continues)

TABLE 4 (Continued)

Panel A. Logit regression: Choice of boutique advisor			
	All	**Public**	**Private**
Pseudo-R^2	0.258	0.342	0.223
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel B. Mean difference in bidder CARs between boutique and full-service advisors			
	One-to-one	**5 nearest**	**Gaussian kernel**
All	0.010**	0.007*	0.008**
	(0.025)	(0.085)	(0.012)
Public	0.004	0.001	0.002
	(0.583)	(0.864)	(0.778)
Private	0.016**	0.010*	0.010**
	(0.022)	(0.093)	(0.033)

average of a 3.0% (4.8%) BHAR over 12 months (24 months) in excess of those hiring full-service banks. These long-term gains are greater in private deals, with a 7.0% (10.6%) improvement over 12 months (24 months).[22]

Given that BHAR estimates are still subject to cross-sectional correlation, we also employ CTPRs to estimate long run returns to acquiring firms, following Mitchell and Stafford (2000). For each month, sample firms enter the monthly portfolio at the announcement month and remain for a duration of 12–24 months. Portfolios are rebalanced monthly, with new acquirers entering the portfolio each month and others exiting the portfolio when they reach the end of the 12- or 24-month period. The monthly portfolio returns are regressed against Fama and French (1993) and Carhart (1997) factors using a time-series regression as in the following equation:

$$R_{p(boutique),t} - R_{p(full-service),t} = \alpha_p + b_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}, \tag{5}$$

where $R_{p(boutique),t} - R_{p(full-service),t}$ is a zero-investment portfolio estimated by the average monthly returns of the boutique portfolio minus those of the full-service portfolio, $R_{m,t} - R_{f,t}$ is the market excess return, *SMB* is the difference in returns between small and large stock portfolios, *HML* is the difference in returns between high– and low–book-to-market equity stock portfolios, and *UMD* is the difference in returns between winner and loser stock portfolios. The intercept, α_p, captures the boutique portfolio's monthly abnormal returns.

Table 6 presents the results for equally weighted (EW) and value-weighted (VW) monthly portfolio returns. The α coefficients that represent the difference in abnormal returns between

[22]The use of value-weighted portfolios produces qualitatively similar results.

TABLE 5 Long-term abnormal returns: Bidder buy-and-hold abnormal returns (BHARs).

This table presents the results from the cross-sectional ordinary least squares regression analysis for a sample of US mergers and acquisitions announced over the period 2000–2016. While all bidders are public firms, the sample is split into all deals and public or private subsets, depending on the target firms' public status. The dependent variable is acquiring firms' equally weighted (EW) BHARs, calculated as follows:

$$BHAR_i = \prod_{t=1}^{T} [1 + R_{i,t}] - \prod_{t=1}^{T} [1 + R_{benchmark,t}],$$

where $R_{i,t}$ is the monthly returns of sample firm i, compounded over the 12- and 24-month period beginning on the announcement date, and $R_{benchmark,t}$ is the compounded returns of a benchmark portfolio selected from the same size/book-to-market category as sample firm *i*. The definitions of the control variables are available in Appendix A. The regressions control for year and industry fixed effects. All control variables are winsorized at 1%, and standard errors are adjusted for heteroscedasticity and bidder clustering. The p-values are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	All		**Public**		**Private**	
	12 months	**24 months**	**12 months**	**24 months**	**12 months**	**24 months**
Boutique	0.030	0.048*	−0.045*	−0.065	0.070***	0.106***
	(0.112)	(0.070)	(0.081)	(0.107)	(0.007)	(0.002)
Run-up	0.052	0.095	-0.016	0.057	0.084	0.115
	(0.327)	(0.160)	(0.829)	(0.630)	(0.229)	(0.154)
Volatility	−2.150*	−4.844***	−1.933	−4.610**	−2.012	−4.473***
	(0.062)	(0.000)	(0.189)	(0.032)	(0.225)	(0.008)
Public deals	−0.044**	−0.055**				
	(0.015)	(0.037)				
Stock deals	−0.067***	−0.072***	−0.098***	−0.126***	−0.043*	−0.048
	(0.000)	(0.004)	(0.000)	(0.001)	(0.053)	(0.142)
Relative size	0.026***	0.034***	0.009	0.020	0.038***	0.044***
	(0.000)	(0.000)	(0.296)	(0.140)	(0.000)	(0.000)
Diversifying deals	−0.009	−0.057**	−0.005	−0.073*	−0.009	−0.040
	(0.661)	(0.027)	(0.849)	(0.056)	(0.723)	(0.240)
Tender offers	−0.013	−0.010	−0.057*	−0.065		
	(0.681)	(0.835)	(0.084)	(0.217)		
Hostile deals	0.084	0.044	0.124*	0.097		
	(0.198)	(0.629)	(0.077)	(0.314)		
Leverage	0.148**	0.232**	0.039	−0.029	0.222***	0.403***
	(0.018)	(0.011)	(0.646)	(0.832)	(0.008)	(0.001)
Constant	0.179***	0.360***	0.225***	0.505***	0.112	0.245*
	(0.008)	(0.000)	(0.009)	(0.000)	(0.271)	(0.060)
Observations	3213	2799	1286	1108	1927	1691

(Continues)

TABLE 5 (Continued)

	All		Public		Private	
	12 months	24 months	12 months	24 months	12 months	24 months
Adjusted R^2	0.022	0.035	0.029	0.033	0.026	0.045
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

boutique and full-service portfolio are positive and significant in both all and private deals. The annualized 12- and 24-month EW (VW) return differentials are 3.6% (7.2%) and 7.2% (14.4%), respectively, for the overall sample and 8.4% (12%) and 14.4% (12%), respectively, for the private subsample.

Overall, the long-run analysis based on both event study methodologies suggests that acquisitions of private targets led by boutique advisors significantly outperform those led by full-service advisors. Our long-run return findings, therefore, corroborate the results from announcement returns: when acquiring firms hire boutique advisors in deals with higher informational asymmetry, such as private deals, the deal outcomes are superior.

4 | WHAT DRIVES BOUTIQUE ADVISORS' VALUE?

Our findings so far indicate that acquirers employing boutique investment banks as their M&A advisor earn higher returns. In this section, we examine further some of the potential explanations behind the superior performance of deals associated with boutique advisors.

4.1 | The role of boutique advisors in mitigating information asymmetry

We have shown that boutique advisors generate superior abnormal returns for acquiring firms' shareholders in private deals where the valuation uncertainty is greater (Officer et al., 2009). Capron and Shen (2007) posit that the lack of publicly available information on private targets increases search costs and the risk of misvaluation, but acquirers selecting targets based on industries they are familiar with or geographic proximities can minimize such risks. Boutique advisors' specialist knowledge in specific industries and regions can therefore be particularly useful for M&A deals subject to such valuation uncertainty.

To examine the relationship between information asymmetry and performance of acquirers hiring a boutique advisor, we utilize two indicators of higher information asymmetry: (i) *cross-industry* deals and (ii) deals where the acquirer lacks *prior acquisition experience* in the target's industry (Graham et al., 2017).[23] We use PSM to determine whether deals subject to higher

[23]If the three-digit SIC code of the acquirer is different from (the same as) the target's, the deal is defined as a cross-industry (same-industry) deal. Prior experience is estimated by the number of acquisitions a bidder has undertaken in a target's industry over the past 3 years before the deal announcement date, based on the three-digit SIC code; the bidder is considered possessing (lacking) prior experience when experience is equal to 1 (0).

TABLE 6 Long-term abnormal returns: Bidder calendar-time portfolio regressions.

This table presents the results from the time-series regression analysis of calendar-time portfolio returns for a sample of US mergers and acquisitions announced over the period 2000–2016. Portfolios are rebalanced by adding firms entering the event at the beginning of each month and excluding firms exiting the portfolio at the end of their 12- to 24-month period. Then the monthly portfolio returns are regressed against Fama and French (1993) and Carhart (1997) factors, as in the following equation:

$$R_{p(boutique),t} - R_{p(full-service),t} = \alpha_p + b_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t},$$

where $R_{p(boutique),t} - R_{p(full-service),t}$ is a zero-investment portfolio estimated by the monthly boutique portfolio returns in excess of the full-service portfolio returns, $R_{m,t} - R_{f,t}$ is the market excess return, *SMB* is the performance difference between small and large stock portfolios, *HML* is the performance difference between high– and low–book-to-market equity stock portfolios, and *UMD* is the performance difference between winner and loser stock portfolios. The intercept, α_p, estimates the boutique portfolio's monthly abnormal return. Panels A to C present the results based on the regression of all deals and public and private subsets, respectively. We report both EW and VW returns. The *p* values are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	12 months		24 months	
	EW	VW	EW	VW
Panel A. All deals				
Alpha	0.003	0.006**	0.003*	0.006**
	(0.130)	(0.048)	(0.064)	(0.042)
RMRF	−0.183***	−0.232***	−0.119***	−0.159**
	(0.000)	(0.008)	(0.004)	(0.043)
SMB	0.075	0.059	−0.022	−0.228*
	(0.537)	(0.695)	(0.844)	(0.056)
HML	0.037	−0.056	0.098	−0.094
	(0.570)	(0.676)	(0.144)	(0.438)
UMD	0.067	−0.315***	0.003	−0.187**
	(0.182)	(0.000)	(0.956)	(0.044)
Calendar Month	215	215	226	226
Adjusted R^2	0.118	0.104	0.059	0.087
Panel B. Public deals				
Alpha	−0.005**	−0.002	−0.003	0.004
	(0.019)	(0.630)	(0.231)	(0.250)
RMRF	−0.301***	−0.057	−0.301***	−0.173*
	(0.000)	(0.591)	(0.000)	(0.092)
SMB	0.048	0.187	0.004	−0.188
	(0.705)	(0.257)	(0.975)	(0.203)
HML	0.400***	0.393**	0.231**	0.019
	(0.000)	(0.041)	(0.029)	(0.911)

(Continues)

TABLE 6 (Continued)

	12 months		24 months	
	EW	VW	EW	VW
UMD	−0.061	−0.389***	−0.126	−0.242**
	(0.453)	(0.000)	(0.185)	(0.038)
Calendar month	214	214	225	225
Adjusted R^2	0.207	0.174	0.157	0.067
Panel C. Private deals				
Alpha	0.007***	0.010***	0.006***	0.005
	(0.006)	(0.008)	(0.010)	(0.178)
RMRF	−0.089	−0.199	−0.014	0.007
	(0.213)	(0.106)	(0.843)	(0.946)
SMB	−0.011	0.407*	−0.135	0.187
	(0.949)	(0.086)	(0.465)	(0.340)
HML	−0.134	−0.483**	0.073	−0.349**
	(0.151)	(0.011)	(0.487)	(0.020)
UMD	0.127*	−0.057	0.093	0.000
	(0.050)	(0.616)	(0.294)	(0.998)
Calendar month	214	214	226	226
Adjusted R^2	0.062	0.138	0.025	0.059

information asymmetry yield better returns when involving boutique advisors. A positive and significant relationship would indicate that boutiques' specialist skills and expertise can be beneficial in mitigating the effects of information asymmetry.

Table 7 presents the results. We find that bidders hiring a boutique advisor in cross-industry M&As gain on average 1.1% higher returns than their full-service counterparts.[24] Similarly, acquirers *without prior acquisition experience* in the target's industry exhibit an average of 0.9% higher returns when hiring boutique advisors. Our findings confirm that bidders pursuing deals with higher information uncertainty have a strong incentive to choose boutique advisors.

4.2 | The role of boutique advisors' industry expertise

Prior studies document that skilled advisors with industry expertise can identify better M&A opportunities and reduce transaction costs, thus creating greater value for their clients (Bowers & Miller, 1990; X. Chang et al., 2016; Graham et al., 2017; Servaes & Zenner, 1996; Song et al., 2013).

[24]In unreported tests, we find that acquirers hiring boutique advisors generate even greater returns with a 1.8% excess returns (at the 5% significance level) over those advised by full-service banks in cross-industry private deals, where information asymmetry is expected to be even higher. In contrast, no performance differential for cross-industry public or same industry public and private deals are observed based on all PSM matching iterations.

TABLE 7 Propensity score matching (PSM): Information asymmetry and bidder CARs.

This table exhibits the results from the PSM on boutique versus full-service deals for a sample of US mergers and acquisitions (M&As) announced over the period 2000–2016. Bidders are public firms, while targets are public or private firms. In testing the impact of financial advisors in M&A deals with higher information asymmetry, we create two subsamples comprised cross-industry deals and deals involving acquirers without prior experience. The variable *cross-industry* is a dummy equal to 1 if the acquirer operates in a different industry from the target, based on the first three digits of the SIC code. The variable *without prior experience* is a dummy equal to 1 if a bidder has not undertaken an acquisition in the current target's industry over the past 3 years before the announcement date, based on the three-digit SIC code. For each subsample, Panel A reports the results of logit regression analysis where the dependent variable is the choice between a boutique and a full-service advisor (a dummy equal to one if the deal is advised by a boutique investment bank, and 0 otherwise). The definitions of the control variables are available in Appendix A. Panel B presents the mean difference in bidder CARs between boutique and full-service deals measured by the ATT, as in Equation (3). These returns are reported based on different matching methods: one-to-one nearest neighbour matching, five-nearest neighbour matching, and Gaussian kernel matching. The regressions control for year and industry fixed effects. All control variables are winsorized at 1%. The *p* values are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Logit regression: Choice of boutique advisor		
	Cross-industry	**Without prior experience**
Bidder size	−0.497***	−0.472***
	(0.000)	(0.000)
Book-to-market	−0.429***	−0.312***
	(0.000)	(0.000)
Run-up	0.112	-0.005
	(0.519)	(0.964)
Volatility	−5.736*	−4.957**
	(0.092)	(0.039)
Public Deals	0.158**	0.135**
	(0.045)	(0.021)
Stock deals	0.065	0.086
	(0.396)	(0.131)
Relative size	−0.335***	−0.345***
	(0.000)	(0.000)
Diversifying deals		0.076
		(0.177)
Hostile deals	−0.406	−0.110
	(0.298)	(0.646)
Leverage	−0.789***	−0.799***
	(0.000)	(0.000)

(Continues)

TABLE 7 (Continued)

Panel A. Logit regression: Choice of boutique advisor		
	Cross-industry	**Without prior experience**
Constant	3.082***	2.668***
	(0.000)	(0.000)
Observations	1815	3246
Pseudo-R^2	0.237	0.244
Industry FE	Yes	Yes
Year FE	Yes	Yes

Panel B. Mean difference in bidder CARs between boutique and full-service advisors			
	One-to-one	**5 nearest**	**Gaussian kernel**
Cross-industry	0.011*	0.010	0.013**
	(0.062)	(0.122)	(0.010)
Without prior experience	0.008*	0.009**	0.009**
	(0.070)	(0.036)	(0.049)

In this section, we investigate whether the value of boutique advisors in M&As can be attributed to their sector-specific knowledge. For this, we first examine the probability of boutique investment banks being industry specialists, using the additive revealed comparative advantage (ARCA) index, a measure of a financial advisor's level of industry expertise, following Graham et al. (2017).

The ARCA index has several advantages over other approaches that simply consider the market share of a particular advisor, based either on the number of deals or on deal value, as a proportion of overall deals in the industry. This is because the ARCA index normalizes a bank's market share in an industry by its relative size in the M&A market. It also ensures that we do not automatically assign more industry expertise to bulge bracket banks, which command a large market share in most industries because of their capacity to advise on more M&A deals.

We measure a bank's industry expertise based on their combined past experience in advising both bidders and targets as a buy-side and sell-side advisor, respectively. This provides a more accurate picture of an advisors' overall expertise and tackles potential underestimation of its expertise when only buy-side advisor experience in an industry is considered.

Industries are classified based on the first three digits of their SIC code, and industry expertise is measured using a 5-year rolling window before the deal announcement. For deals involving multiple advisors, each advisor is credited with the deal as part of their experience. Finally, we eliminate advisors who have advised on only one deal over a 5-year window, since they would be misclassified as industry specialists by the index. The ARCA index is estimated as follows:

$$ARCA_j^i = \left(\frac{X_j^i}{X^i}\right) - \left(\frac{X_j^A}{X^A}\right), \tag{6}$$

where $ARCA_j^i$ is the industry expertise of $advisor_i$ in $industry_j$, X_j^i is the value of M&A deals advised by $advisor_i$ in $industry_j$, X^i is the value of M&A deals advised by $advisor_i$ across all industries, X_j^A is the total value of M&A deals advised by all advisors in $industry_j$, and X^A is the total value of M&A deals advised by all advisors across all industries.

If $ARCA_j^i$ is greater than zero, $advisor_i$ is classified as an industry specialist in $industry_j$, as it has a larger share of its acquisition advisory portfolio in $industry_j$ than the average bank. However, if $ARCA_j^i$ is less than or equal to zero, $advisor_i$ is considered a nonindustry specialist in $industry_j$.

We first compare the mean ARCA index between boutique and full-service advisors in Table 8. Our results show that, on average, boutique advisors' industry expertise is significantly greater than that of full-service banks. We also find that a significantly larger proportion of boutique advisors have specialized sector knowledge, since 85.6% of boutiques are classified as industry specialists, compared with 61.5% of full-service advisors. Further, we perform probit regression analysis to examine the likelihood of a boutique being an industry specialist. Panel A of Table 9 shows that both the ARCA index and the industry specialist variable are significantly and positively related to the boutique dummy (at the 1% level), implying that boutique advisors are more likely to be industry specialists.

Lastly, we use PSM to compare the performance of acquirers hiring an *industry specialist boutique*, a dummy equal to one if a boutique advisor is an industry specialist. The results presented in panel B of Table 9 suggest that industry specialist boutiques are associated with higher CARs on average by 0.6% in all deals and 1.7% in private deals. Our findings provide evidence that boutique advisors' industry expertise plays an important role in creating value in M&As.

4.3 | Conflicts of interest and advisory quality

Another source of value creation that we explore is the independence of boutique investment banks' advisory services. Unlike full-service banks, which are often described as one-stop-shops for

TABLE 8 Additive revealed comparative advantage (ARCA) index and proportion of industry specialists.

This table presents the mean ARCA index and proportion of industry specialists for the boutique and full-service subsamples. The *ARCA index* is generated using the proportion of an advisor's market share (deal value) in its current acquirer client's industry (based on the first three digits of the SIC code), divided by its total deal value across all industries over the past 5 years before the deal announcement. An advisor's market share is then normalized by its relative size (total deal value in the industry divided by the total deal value across all industries) in the mergers and acquisitions market. The variable *industry specialist* is a dummy equal to 1 if the ARCA index of an advisor is greater than 0. *N* denotes the number of observations for boutique and full-service subsets. The *p* values for the mean differences between the two advisor groups are reported in the last column. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	Boutique (1)	**Full-service (2)**	**Difference (1) – (2)**	***p* Value**
Mean ARCA	0.303	0.036	0.267***	0.000
Proportion of industry specialist (ARCA > 0)	0.856	0.615	0.241***	0.000
N	1584	2773		

TABLE 9 Industry expertise of boutique advisors.

This table presents the results of the analysis on boutique advisors' industry expertise for a sample of US mergers and acquisitions (M&As) announced over the period 2000–2016. Panel A reports the results from probit regression where the dependent variable is boutique, which is a dummy equal to 1 if the deal is advised by a boutique investment bank, and 0 otherwise. The level of industry expertise of an advisor is estimated by ARCA index, which is generated using the proportion of an advisor's market share (deal value) in its current acquirer client's industry (based on the first three digits of the SIC code), divided by its total deal value across all industries over the past 5 years before the deal announcement. An advisor's market share is then normalized by its relative size (total deal value in the industry divided by the total deal value across all industries) in the M&A market. The variable industry specialist is a dummy equal to 1 if the ARCA index of an advisor is greater than 0. Panel B exhibits the results from the PSM on the performance of acquirers advised by industry specialist boutiques versus full-service banks. The propensity scores are generated using logit regression analysis, where the dependent variable is the choice between industry specialist boutiques and full-service advisors. Then boutique deals (treatment group) are matched with full-service deals (control group) based on similar acquirer and deal characteristics. The mean difference in bidder CARs between the two advisor groups is measured by the ATT, as in Equation (3). These returns are reported based on different matching methods: one-to-one nearest neighbour matching, five-nearest neighbour matching, and Gaussian kernel matching. The control variables (omitted from this table) are selected based on acquirer and deal characteristics and are defined in Appendix A. The regressions control for year and industry fixed effects. All control variables are winsorized at 1%. The *p* values are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Probit regression: Industry expertise of boutique advisors

	(1)	(2)
ARCA	2.294***	
	(0.000)	
Industry specialist		0.627***
		(0.000)
Observations	3924	3924
Pseudo-R^2	0.353	0.284
Control variables	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

Panel B. PSM: Mean difference in bidder CARs between industry specialist boutique and full-service advisors

	One-to-one	5 nearest	Gaussian kernel
All	0.004	0.005	0.008*
	(0.462)	(0.309)	(0.075)
Public	0.004	0.009	0.003
	(0.696)	(0.287)	(0.735)
Private	0.019***	0.014**	0.017**
	(0.006)	(0.026)	(0.028)

offering variety of financial services to their clients, boutique advisors are less prone to conflicts of interest given their focus on corporate finance advisory. In this section, we empirically examine the association of financial advisors with conflicts of interest and its impact on deal outcomes.

Conflicts of interest in acquisitions can arise when financial advisors have incentives to pursue potentially value-destroying deals for their clients for their own gains. Examples of such cases have been documented by the literature. McLaughlin (1990, 1992) argues that contingency-based fee contracts upon deal completion can undermine value creation by promoting conflicts of interest between advisors and clients. Advisors under such contracts can complete mergers for the purpose of earning lucrative advisory fees, without necessarily offering their best efforts to create value for their clients. Similarly, Rau (2000) finds that the contingent fee structure provides investment banks an incentive to focus more on completing deals than on enhancing deal quality. Accordingly, he finds that the reputation of investment banks based on their market share is positively associated with both contingent fee payments and the deal completion rate, but negatively related to acquirers' postacquisition performance in tender offers. Bao and Edmans (2011) also find that bulge bracket banks associated with lower average CARs tend to take on higher proportions of value-destroying deals than small deals with positive returns.

Since limited information on the nature of acquirers and financial advisors' contractual arrangements is available, we focus on examining the following: (i) the likelihood of boutique and full-service banks engaging in bad (value-destroying) deals and (ii) the likelihood of acquirers hiring boutique advisors withdrawing from such deals. To examine these probabilities, we define *bad deals* as M&A transactions with acquirer CARs in the bottom quintile (20th percentile) following Chen et al. (2007). The mean bidder CAR in the bottom quintile after winsorization is −11%, with the lowest being −24%.

Table 10 compares the proportion of bad/good deals for boutique and full-service advisors. Full-service advisors tend to take on significantly higher proportions of bad deals than boutique advisors do, although the proportion of *good deals* (CARs in the top 20th percentile) is similar between the two groups. The probit analysis in Panel A of Table 11 further shows that hiring a full-service advisor in private deals is positively associated with bad deals (at the 5% level),

TABLE 10 Proportion of bad deals: Boutique versus full-service advisors.

This table presents the proportions of bad/good deals for (1) boutique and (2) full-service advisors. We define *bad deals* as transactions that are associated with the bottom 20th percentile of acquirer CARs based on a quintile division, while *good deals* are those in the top 20th percentile. The *p* values for the mean differences between the two advisor groups are reported in the last column.

	No. of obs.	Proportion of bad or good deals
Bad deals		
(1) Boutique	1664	0.176
(2) Full-service	2900	0.214
p Value, H_0: Diff. in prop. of bad deals $(1)-(2)<0$		0.001
Good deals		
(1) Boutique	1664	0.194
(2) Full-service	2900	0.203
p Value, H_0: Diff. in prop. of good deals $(1)-(2)>0$		0.791

TABLE 11 Probit regression analysis: Bad deals and likelihood of withdrawal.

This table examines the association between bad deals and two groups of financial advisors: boutique versus full-service banks for a sample of US mergers and acquisitions announced over the period 2000–2016. While all bidders are public firms, the sample is split into (1) all deals and (2) public deals or (3) private deals, depending on the target firms' public status. Panel A presents the results from the probit regression analysis on the probability of full-service advisors engaging in bad deals. The dependent variable is bad deal, a dummy equal to 1 if an acquirer CAR belongs to the bottom 20th percentile. The variable of interest in this regression is full-service, which is a dummy equal to 1 if the deal is advised by a full-service bank, and 0 otherwise. Panel B presents the results from the probit regression analysis on boutique advisors' likelihood of withdrawing from a bad deal. The dependent variable is the withdrawn dummy, equal to 1 if an announced acquisition deal is withdrawn on a later date, and 0 if completed. The variable of interest in this regression is the interaction variable between boutique and bad deals (Boutique × bad deals). Boutique is a dummy equal to 1 if the deal is advised by a boutique investment bank, and 0 otherwise. Competing bids is a dummy equal to 1 if the deal involves more than one bidder. Deal premium is the difference between the offer price and the target's market value 4 weeks before the acquisition announcement date, scaled by the latter. The control variables (omitted from this table) are selected based on firm and deal characteristics and are defined in Appendix A. The regressions control for year and industry fixed effects. All control variables are winsorized at 1%. The *p* values are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	All	**Public**	**Private**
	(1)	**(2)**	**(3)**
Panel A. Probit regression: Full-service advisors and the probability of bad deals			
Full-service	0.086	−0.009	0.168**
	(0.167)	(0.928)	(0.030)
Observations	3924	1552	2370
Pseudo-R^2	0.136	0.198	0.103
Control variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel B. Probit regression: Likelihood of withdrawing from a bad deal			
Boutique	−0.112	−0.122	−0.086
	(0.315)	(0.496)	(0.603)
Bad deals	0.178	0.271*	0.113
	(0.111)	(0.073)	(0.556)
Boutique × bad deals	0.135	0.097	0.452*
	(0.414)	(0.662)	(0.070)
Competing bids	1.361***	1.221***	2.766***
	(0.000)	(0.000)	(0.000)
Deal premium		−0.001	
		(0.702)	
Observations	4071	1507	2403
Pseudo-R^2	0.303	0.358	0.216

TABLE 11 (Continued)

	All	**Public**	**Private**
	(1)	**(2)**	**(3)**
Control variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

suggesting the probability of destroying shareholder value increases with full-service banks. Conversely, Panel B of Table 11 indicates that acquirers hiring boutique advisors are more likely to reflect the negative market reaction to announcement returns and withdraw from a bad deal in the acquisition of private targets.[25]

While these findings offer additional insights on why boutique-led private deals yield better returns, the question that naturally arises is why the link between full-service advisors and bad deals, our proxy for conflicts of interest, is observed only in private deals. As noted by Golubov et al. (2012), public deals are associated with greater reputational exposure for financial advisors, largely due to the press and media coverage, which raises their stakes in league table rankings. Thus, it is possible that full-service banks have significant incentive to advise a client against a value-destroying deal when the acquisition involves a public target.

5 | FINANCING AS A DRIVER OF ADVISOR CHOICE

In this paper, we find that boutique advisors deliver superior M&A outcomes mainly in private deals through their specialist industry knowledge, ability to mitigate information asymmetry, and independence of their advisory service from conflicts of interest. These relative advantages of hiring boutique advisors may prompt a question regarding what aspects of full-service banks still motivate many acquirers to hire them as M&A advisors. Prior literature documents that acquirers often hire full-service banks as their M&A advisors because of their pre-existing relationships through lending, underwriting, or other customer relationships (Allen et al., 2004). The size of a deal is another crucial motive for choosing full-service over boutique advisors for their reputation and a certification effect (Song et al., 2013). In this section, we additionally consider an aspect that has not been empirically examined before, which is full-service banks' acquisition financing capabilities.

M&A deal financing is a highly profitable business and has traditionally provided a significant source of full-service banks' revenue.[26] Although more recently the acquisition financing landscape has become more complex with the significant involvement of nonbanks, full-service banks still command the lion's share in the deal financing segment relative to boutique advisors. Hence, setting advisor skills and expertise aside, one of the apparent reasons why full-service banks could be preferred in some deals is their financial resources and capabilities.

To investigate the relationship between acquirers' financing needs and advisor choice, we obtain data on Acquirer Financial Advisor Assignments from the SDC Platinum M&A Database, through

[25]For this regression, we include the additional control variables, *competing bids* and *deal premium* that are known to affect withdrawal decisions.

[26]See S&P Global Market Intelligence, 2 August 2021, 'M&A leveraged loan issuance sets record, driven by private equity surge'.

TABLE 12 Probit regression analysis: Acquirers' financing needs and advisor selection.

This table presents the results from the probit regression analysis on acquirers' financing needs and advisor selection for a sample of US mergers and acquisitions announced over the period 2000–2016. Bidders are public firms, while targets are public or private firms. The dependent variable in models (1) and (2) is the full-service dummy, equal to 1 if the deal is advised by a full-service bank, and 0 otherwise. The variable *acquisition financing* is a dummy equal to 1 if an acquirer's financial advisor arranged or provided financing for the transaction. Cash deals is a dummy equal to 1 if the transaction is fully paid by cash. The control variables are selected based on firm and deal characteristics and are defined in Appendix A. The regressions control for year and industry fixed effects. All control variables are winsorized at 1%. The *p* values are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	Full-service (1)	**Full-service (2)**
Acquisition financing	1.603***	
	(0.000)	
Cash deals		0.114**
		(0.037)
Constant	−2.733***	−2.811***
	(0.000)	(0.000)
Observations	3924	3924
Pseudo-R^2	0.265	0.255
Control variables	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

which we identify whether an acquirer's advisor has arranged for or directly provided financing. Of the 5010 deals in our sample, advisors in 183 deals appear to have arranged or provided acquisition financing for an acquirer. Table 12 presents the results of probit regression analyses.

Model (1) shows that the *acquisition financing* variable—which is equal to 1 if the acquirer's financial advisor arranged or provided financing—is positively and significantly associated with hiring a full-service bank (at the 1% level). Similarly, acquirers financing the entire deal with cash (*cash deals*) are more likely to select full-service advisors (at the 5% level), as in model (2). These findings are consistent with our conjecture that one of the key drivers for hiring full-service banks is their deal financing capabilities.

6 | ADDITIONAL ROBUSTNESS TESTS

In this section, we conduct additional tests to examine whether our results are robust to alternative specifications and methodologies.[27]

[27]The test results in this section are not tabulated but are available upon request.

6.1 | Matching quality diagnostics

We use PSM to control for the effect of observed confounding on acquirer performance. After the treatment, the quality of matching is assessed by comparing the similarity of matched variables (acquirer and deal characteristics) between treated and untreated subjects. Various matching quality diagnostics tests are employed to confirm the matching quality including the standardized bias, *t*-test, pseudo-R^2, and the test of joint significance (*F*-test). The results are reported in Appendix C.[28]

The first column of the table in Appendix C displays the variable name, while the second column indicates the matching status: *unmatched* (U) is before matching and *matched* (M) is after matching. The third and fourth columns exhibit the mean value of the corresponding variables for the treatment and control groups, respectively, and *% bias* is the standardized bias, which measures the mean variance (difference) in matched deal characteristics. The bias is considerably higher before matching, but significantly smaller after matching. The percentage reduction in bias, *% reduction,* in the next column reflects how much reduction in bias between the two groups has been achieved after matching. In our case, the overall bias is fairly low for all covariates, and the combined mean bias (*MeanBias*) is only 1.4%, indicating a high level of similarity in matched deal characteristics. The *t*-test results also present no significant discrepancies in the characteristics of matched deals, excluding the *bidder size* variable by a marginal difference. Further, the *pseudo-R^2* value (Sianesi, 2004) is significantly low after matching, indicating no systematic differences in covariates. Finally, the *F*-test on the joint significance (χ^2) indicates that all confounders are well balanced after matching.

Based on these diagnostics tests, we conclude that a good level of balancing between the two groups has been achieved through PSM. We further present the distribution comparison of acquirer and deal characteristics before and after matching in the box chart and density graph in Figure 3.

6.2 | Deals advised by both boutique and full-service advisors

We additionally perform empirical analysis including 934 deals advised by both boutique and full-service banks. These deals were previously excluded from our analysis to avoid any measurement error that could arise from crediting both advisors equally while each advisor's level of contribution to a deal can be different. Our results continue to hold when including these multiple advisor deals.

6.3 | Frequent acquirers

Macias et al. (2020) document that a small number of frequent acquirers often commend the majority of deals in the M&A sample, which could bias CAR-based outcomes. To address this concern, we perform empirical analysis excluding frequent bidders and verify the consistency of our findings for boutique advisors. Following Fuller et al. (2002) and Macias et al. (2020), we

[28]Diagnostics tests are implemented after each PSM based on different matching methods (nearest neighbour matching and kernel matching) and subsample analysis (all, public, and private deals). To demonstrate overall matching quality, we present only the test results of overall deals with kernel matching. Note that the other diagnostic test results are similar to those in the table in Appendix C.

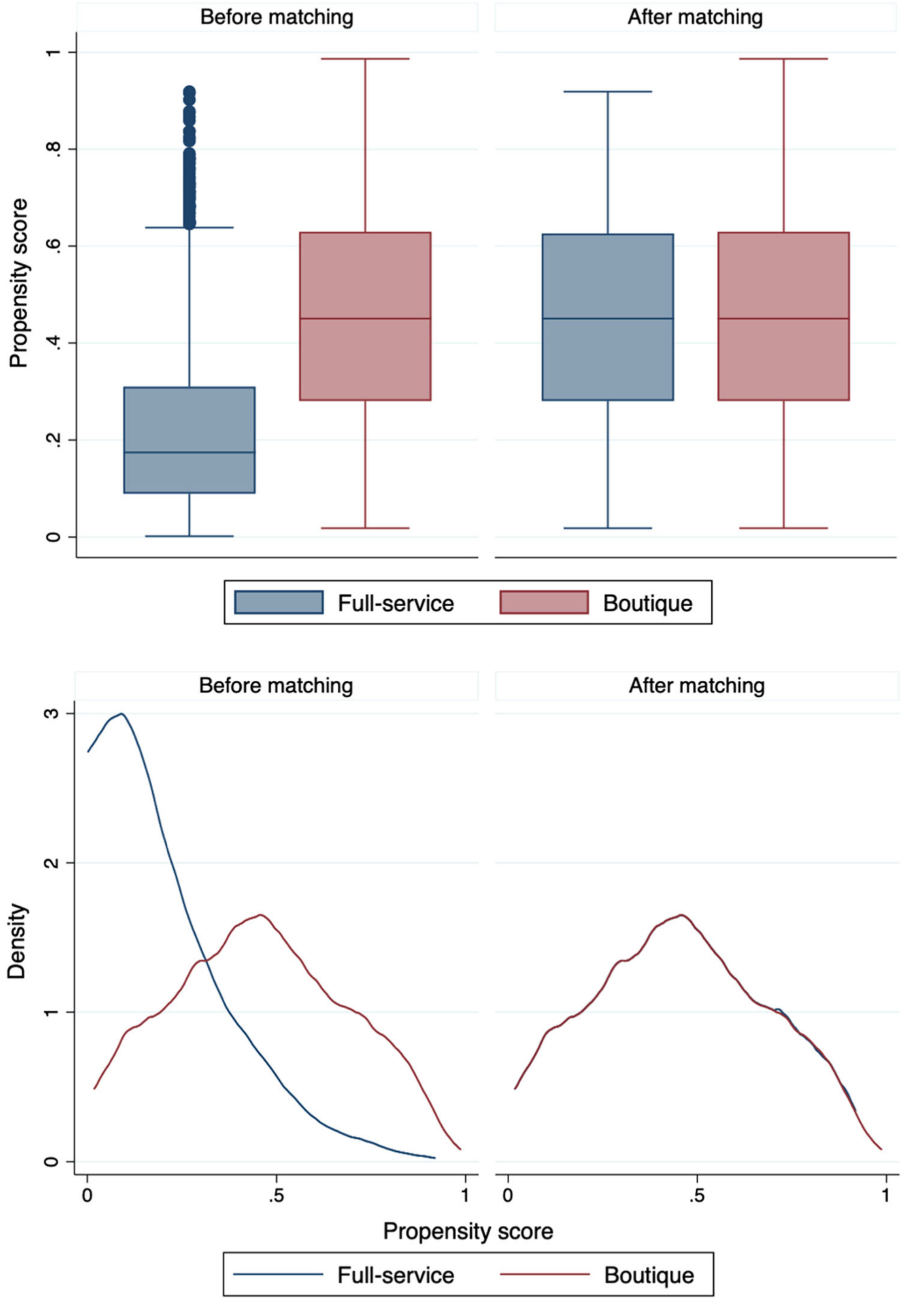

FIGURE 3 Propensity score matching (PSM) quality. The following panels present the overall discrepancy (similarity) of acquirer and deal characteristics between boutique and full-service deals before (after) PSM in a box graph and line chart, respectively. Both panels show that the acquirer and deal characteristics between the two groups become similar after matching. [Color figure can be viewed at wileyonlinelibrary.com]

define frequent acquirers as those who have acquired five or more targets within a 3-year period. This process identifies 26 frequent acquirers along with 118 associated transactions to be removed from our regression analysis. We further exclude 88 clustered takeovers in which a bidder acquires two or more firms within 5 days, to isolate its return for a particular target. Our results do not change when removing transactions by frequent acquirers.

6.4 | Boutique advisor classification

We reclassify financial advisors in our sample following the classification method of Song et al. (2013), whereby boutique investment banks are defined as those focusing on M&A advisory-services-only and having specialized industries. Then, we test whether our results continue to hold when we follow the more traditional classification approach. After removing from our original list of boutique advisors those who have engaged or are known to engage in wealth/asset management, underwriting, private placements, or brokerage services such as sales, trading, research, and lending, we are left with 134 boutique advisors. Even with a different advisor classification approach, both the OLS and PSM estimates yield consistent results with our original findings.

6.5 | Endogenous switching regression analysis

Alternatively, we perform endogenous switching regression to control for selection bias. Like Heckman's (1979) model, this method is useful in controlling for unobservable bias, but, more importantly, it can also derive counterfactual (unobserved) outcomes, had an acquirer hired a different advisor. Endogenous switching regression involves a two-stage model based on the maximum likelihood estimation: the first stage measures the selection of a financial advisor between boutique and full-service, and the second stage estimates acquirer abnormal returns, separately, for the boutique and full-service subsamples in the OLS regression. Then, we use these estimates to derive counterfactual outcomes as well as differences in mean bidder CARs between observed and counterfactual returns. This switching regression indicates that using a full-service advisor for a boutique deal would have resulted in an average 3.3% decline in the bidder CAR, while hiring a boutique advisor for a full-service deal would have led to a 1.4% improvement.

6.6 | Performance of boutique advisors over different sample periods

We observe significantly indifferent performance between acquirers hiring a boutique advisor and those hiring a top-tier full-service advisor in public deals, unlike the study of Golubov et al. (2012), where top-tier deals outperform boutique deals. We presume that the contrasting results in our studies could be attributed to discrepancies in sample period rather than the use of a different classification methodology or empirical test. In particular, the inclusion of the post-2008 financial crisis period, where boutique advisory firms experience unparalleled growth in market share and revenue from M&A advisory services, could have largely contributed to their enhanced performance. To test whether financial advisors experience change in performance over different sample periods, we separately examine the performance of boutique versus top-tier deals during the period 1995–2006 and 2000–2016. The former sample period is that of Song et al. (2013), which ends in 2006, since Golubov et al. employ their advisor classification data. The latter is our sample period.

Following Golubov et al. (2012), we classify top-tier advisors as the top five or eight banks, based on transaction value, and perform multinomial OLS regression and Heckman's two-stage analysis to gauge the difference in deal outcomes between top-tier versus boutique advisors. We find that acquirers hiring top-tier advisors in public deals significantly outperform those hiring boutique advisors during the period 1995 to 2006, but such a performance differential dissipates over the post-2000 period. Our findings imply that, over time, boutique advisors have achieved significant improvement in advisory quality, even in public deals, explaining their increasing reputation and market share.

6.7 | The impact of small-scale boutique advisors on M&A deal outcome

We consider whether the superior performance of boutique advisors can be attributed to their small-scale operations, since the smaller the advisor, the more senior-level attention their clients may receive, resulting in in-depth advice and potentially in better deal outcomes. Most boutique investment banks are private firms without publicly available firm-level information; thus, we use the average deal value each advisor has undertaken over the sample period as the proxy for advisor size. Advisors are then categorized into quintiles from the bottom 20th to the top 20th percentile based on their mean deal value. We find that approximately 78% of boutique advisors (165 out of 212) are small boutiques, belonging to the bottom quintile of the size group, with the mean deal value of $147.3 million. It appears that these small boutiques do not generate higher abnormal returns, over and above the returns of average boutique deals. Hence, we conclude that what drives value creation for boutique advisors is their unique characteristics highlighted throughout this paper, not the size of their operation being small.

7 | CONCLUSION

With the increasing demand for industry specialization in strategic mergers and diversified sources of funding, corporate clients have turned their eyes to highly specialized advisory boutiques for M&As. This study investigates the sources of advisory boutiques' increasing market share and reputation and provides new empirical evidence on the value of boutique investment banks.

Based on the analysis of 3-day bidder announcement returns, we find that boutique advisors' growing reputation is attributable to the superior quality of their services, with economically significant value creation for acquirer shareholders. In particular, boutique advisors generate higher CARs relative to full-service advisors in deals with higher information asymmetry, such as acquisitions of private targets, cross-industry mergers, and deals involving acquirers without prior acquisition experience in the target industry. We also consider the long-term effects of acquirer shareholder wealth and find that shareholders earn higher returns in the long run when involving boutique advisors.

Our results continue to hold after controlling for sample selection bias using Heckman's two-step analysis and PSM. Finally, we provide the first empirical evidence that the sources of boutiques' value creation originate from their strong industry expertise. They are also less prone to conflicts of interest and are more likely to withdraw from value-destroying deals. Our study offers evidence in support of the increasing demand for boutique investment banks in the financial advisory space and their unique abilities to drive value creation.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX A: VARIABLE DEFINITIONS

Variable name	Description
Bidder size	Acquirers' market value of equity (in millions of US dollars) 4 weeks before the acquisition announcement (CRSP). The log of bidder size is used in regression analyses.
Book-to-market	Acquirers' book value of equity at the fiscal year-end before the announcement (Compustat), divided by their market value of equity 4 weeks before the announcement (CRSP).
Run-up	Acquirers' value weighted market-adjusted excess return over the 200-day period (−205, −6) before the acquisition announcement (CRSP).
Volatility	Standard deviation of acquirers' daily stock returns (market adjusted) between 205 and 6 days before the announcement date (CRSP).
Leverage	Acquirers' total debt divided by the book value of total assets at the fiscal year-end before the announcement (Compustat).
Deal value	Transaction value in millions of U.S. dollars (SDC).
Relative size	Deal value (SDC) divided by the acquirer's market value of equity 4 weeks before the announcement (CRSP).
Tender offers	A dummy that takes the value of 1 when the acquisition technique includes a tender offer (SDC).
Public deals	A dummy that takes the value of 1 when the target firm's public status is public (SDC).
Private deals	A dummy that takes the value of 1 when the target firm's public status is private (SDC).

(Continues)

Variable name	Description
Diversifying deals	A dummy that takes the value of 1 if the first 2 digits of the bidder's SIC code do not match those of the target's SIC code, and 0 otherwise.
Hostile deals	A dummy that takes the value of 1 when the acquisition method is hostile (SDC).
All cash	A dummy that takes the value of 1 if 100% of the transaction was paid by cash (SDC).
All stock	A dummy that takes the value of 1 if 100% of the transaction was paid by stock (SDC).
Mixed payments	A dummy that takes the value of 1 if the transaction was paid by both cash and stock (SDC).
Stock deals	A dummy that takes the value of 1 if the transaction involves a stock payment (SDC).
Competing bids	A dummy that takes the value of 1 if the deal involves more than one bidder.
Premium	The percentage difference between the offer price and the target's market value 4 weeks before the acquisition announcement date (SDC), winsorized between 0 and 2, following Officer (2003).
CAR (−1, +1)	Acquirers' value-weighted 3-day CARs surrounding the announcement date. The CAR is generated using the bidder's stock return minus the benchmark portfolio return over the event window. The benchmark is estimated using the market model over the period beginning −295 days and ending −45 days before the announcement date.

APPENDIX B: NUMBER OF MATCHED DEALS FROM PSM

The following table presents the number of deals matched based on PSM for all deals and public and private subsamples. The column with the heading *Treated* includes deals advised by the boutique group, and that with the heading *Control* includes deals advised by the full-service group.

Matching methods	Treated	Control
All deals		
One-to-one	1418	668
5 nearest	1418	1614
Gaussian kernel	1344	2466
Public deals		
One-to-one	535	223
5 nearest	535	548
Gaussian kernel	513	1017
Private deals		
One-to-one	883	423
5 nearest	883	1011
Gaussian kernel	816	1442

APPENDIX C: MATCHING QUALITY DIAGNOSTICS TESTS

The following table presents the diagnostics test results before and after performing PSM. The mean values of each of the control variables based on unmatched and matched deals are displayed under the columns labelled *Treated* (boutique deals) and *Control* (full-service deals). *% bias* measures the mean variance in each control variable between the treated and control groups, while *MeanBias* and *MedBias* (median) measure joint variance. *% reduction bias* shows how much reduction in bias has been achieved after matching. *t-Test* (*chi2*) estimates the (joint) significance of differences in matched variables. *Pseudo-*R^2 tests whether there are systematic differences in characteristics between the treated and control groups after matching.

Variable	Unmatched / Matched	Mean: Treated	Mean: Control	% bias	% reduction |bias|	*t*-Test: *t*	*t*-Test: $p > \|t\|$
Bidder size	U	5766.4	16,618.0	−28.7		−8.29	0.000
	M	5794.4	8915.3	−8.2	71.2	−2.90	0.004
Book-to-market	U	0.568	0.458	32.2		9.74	0.000
	M	0.565	0.567	−0.5	98.3	−0.13	0.895
Run-up	U	0.001	−0.004	2.2		0.64	0.521
	M	0.000	−0.004	2.0	7.0	0.53	0.598
Volatility	U	0.025	0.025	1.8		0.53	0.594
	M	0.025	0.025	v2.4	−39.2	−0.62	0.538
Public Deals	U	0.377	0.406	−5.8		−1.76	0.079
	M	0.378	0.353	5.2	10.2	1.41	0.158
Stock deals	U	0.728	0.630	21.1		6.28	0.000
	M	0.726	0.714	2.7	87.1	0.75	0.456
Relative size	U	0.303	0.372	−12.6		−3.70	0.000
	M	0.304	0.304	−0.1	99.0	−0.04	0.969
Diversifying deals	U	0.300	0.356	−12.0		−3.59	0.000
	M	0.301	0.312	−2.4	79.9	−0.65	0.515
Hostile deals	U	0.006	0.019	−11.4		−3.22	0.001
	M	0.006	0.007	−0.4	96.8	−0.13	0.894
Leverage	U	0.143	0.217	−43.2		−12.64	0.000
	M	0.144	0.146	−1.4	96.8	−0.42	0.678

Sample	Pseudo-R^2	LR χ^2	$p > \chi^2$	MeanBias	MedBias
Unmatched	0.131	674.30	0.000	11.6	10.1
Matched	0.005	18.08	0.996	1.4	0.8