Journal of Financial Economics 146 (2022) 230–255

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Peer selection and valuation in mergers and acquisitions

Gregory W. Eaton[a], Feng Guo[b], Tingting Liu[b,*], Micah S. Officer[c]

[a] Oklahoma State University, Spears School of Business, Stillwater, OK, 74078, USA
[b] Iowa State University, Ivy College of Business, Ames, IA, 50011, USA
[c] Loyola Marymount University, College of Business Administration, Los Angeles, CA, 90045, USA

ARTICLE INFO

Article history:
Available online 13 September 2021

JEL classification:
G34
G24

Keywords:
Mergers and acquisitions
Valuations
Investment banks
Comparable companies analysis
Takeover premiums

ABSTRACT

Using unique data, this paper examines investment banks' choice of peers in comparable companies analysis in mergers and acquisitions. We find strong evidence that product market space is amongst the most important factors in peer selection, but Standard Industrial Classification (SIC) codes, particularly three and four digit codes, do a poor job of categorizing related firms in this setting. Banks strategically select large, high growth peers with high valuation multiples, factors that are also positively related to premiums. Our evidence is consistent with target-firm advisors selecting peers with high valuation multiples to negotiate higher takeover prices.

1. Introduction

Comparable companies analysis (CCA), which derives an estimate of firm value from peer firms' valuation multiples, is one of the most popular methods of valuation in investment banking. Investment banks and other practitioners use CCA in sell- and buy-side equity research, as well as in the analysis of large corporate transactions such as initial public offerings (IPOs) and mergers and acquisitions (M&As). Further, evidence shows that private equity (PE) investors heavily rely on comparable companies (comps)–based valuation approaches, which even outpaces their use of the discounted cash flow (DCF) approach (Gompers, Kaplan, and Mukharlyamov, 2016). Despite the popularity of CCA in practice, academic evidence on the use and execution of this technique is limited, and the literature contains little discussion about the incentive effects and value implications associated with it. The research that does exist studies the accuracy of CCA (Alford, 1992; Kaplan and Ruback, 1995; Kim and Ritter, 1999), uses CCA to value private firms (Beatty, Riffe, and Thompson, 1999; Officer, 2007), or models an approach for choosing comparable firms (Bhojraj and Lee, 2002).

We aim to provide novel evidence by studying a crucial step in estimating value with CCA: the selection of peer firms. We focus on M&A transactions, which are amongst the most important undertakings that firms conduct. In particular, we study CCA by target firm advisors in M&As, and our main research question is: What factors appear to influence the selection of peer, or comparable, firms? Numerous relevant incentive effects appear in the peer selection process.[1] We take advantage of one important institutional detail in our empirical work. In M&A deals, the target firm is often required to disclose to its shareholders whether the deal is fair or not on the basis of valuation (see, e.g., Bebchuk and Kahan, 1989; Cain and Denis, 2013;

* Corresponding author.
E-mail addresses: gregory.eaton@okstate.edu (G.W. Eaton), fengguo@iastate.edu (F. Guo), ttliu@iastate.edu (T. Liu), micah.officer@lmu.edu (M.S. Officer).

[1] For an example of practitioner concerns about these incentive effects, see the section titled "Fairness opinions" in Matt Levine's *Money Stuff* newsletter from Bloomberg dated July 31, 2020 (https://www.bloomberg.com/opinion/articles/2020-07-31/apple-stock-will-get-cheaper).

https://doi.org/10.1016/j.jfineco.2021.09.006

Davidoff, Makhija, and Narayanan, 2011; Kisgen, Qian, and Song, 2009; Liu, 2020), and CCA usually plays a prominent role in that determination. This communication is reported in Securities and Exchange Commission (SEC) filings, which contain a rich trove of data about which firms are considered comparable to a particular target.

The selection process is almost surely driven by the target's principal advisor in the M&A transaction, which is typically an investment bank or advisory firm. In this paper we examine whether the characteristics of peer firms chosen by target firms' investment banks suggest that banks choose peers to aid in the negotiation of a higher offer price for target firm shareholders or choose peers that help with the completion of a proposed deal. The latter enables banks to collect their advisory fees, a large fraction of which are typically conditional on deal completion.

The incentive to select peers in such a way that helps the target in negotiation with a prospective bidder would imply that the target's investment bank chooses peers that, all else equal, have higher valuation multiples, which make the perceived value of the target firm appear higher [see article cited in footnote 1 and Davidoff (2006)]. Conversely, the incentive to select peers in a way that helps with the closing of a transaction (and the bank's collection of its advisory fees) would imply that the investment bank chooses peers that, all else equal, have lower valuation multiples. This would make the bidder's offer appear more generous to target shareholders, increasing the probability that they accept the offer. Because the investment bank advising the target firm in the transaction has significant discretion in the choice of peers, which of the incentive effects dominates is an empirical question and is the main focus of our study.

Using hand-gathered data from SEC filings, we begin by studying the role that industry membership plays in peer selection. We show that, based on SIC codes, particularly three- and four-digit codes, a surprisingly large portion of peer firms chosen in CCA by the target firms' advisory bankers have a different industry classification than their target firms. For example, nearly half of the chosen comps have different four-digit SIC codes than the target firms. However, this does not mean that peers are poorly chosen in many deals. Instead, using categorical data, such as SIC codes, appears to underrepresent industry overlap in many cases.

For deals in which chosen comps have different SIC codes than the target or the bidder, we find that product similarity scores (Hoberg and Phillips, 2010, 2016), a continuous measure of industry overlap between peers and the merging firms, range from 0.097 to 0.150, which is substantially higher than average product similarity score between two random firms in the Compustat universe (0.038). Thus, industry affiliation appears to play an important role in peer selection in CCA, which is consistent with industry membership being an important determinant of key value drivers, such as firm risk and growth.[2] One way of interpreting our results in this area is that they are generally consistent with skepticism in the finance literature about the usefulness of relying on SIC codes to capture industry relatedness of firms (e.g., Kahle and Walkling, 1996; Hoberg and Phillips, 2010).

We go on to study a number of factors (size, growth, asset efficiency, valuation multiples) that can influence the selection of peer firms. Our strong and robust results also suggest that investment banks appear to strategically select peers that are large, high growth firms with relatively high valuation multiples. Further, valuation multiples of chosen comps are positively related to deal premiums and target stock announcement returns. This evidence is consistent with the advisory banks boosting the target firm's perceived value by selecting high profile, well-performing peers with high valuations to help their client (the target) negotiate a higher offer price from the bidder. These results are less consistent with banks rubber-stamping the offer price to facilitate deal completion.

We examine some additional incentive effects in the peer selection process, that is, whether the results also hold in a sample of management buyout deals. Management buyouts present a setting where concerns about agency problems are particularly germane because the target firm's managers have an incentive to purchase the firm from shareholders at the lowest possible price. Our results in this subsample suggest that peers selected in buyout deals tend to have lower valuation ratios and weaker operating performance. However, these results weaken once we control for bidder characteristics. Thus, although we are not able to reach a definitive conclusion, we provide some evidence that investment banks could strategically select low-value peers to justify the lower premiums offered in buyout deals (Bargeron, Schlingemann, Stulz, and Zutter, 2008).

We also look for incentive effects in the peer selection process in advisor reputation and in time periods surrounding an important regulatory change that led to increased disclosure of banks' conflicts of interest [Financial Industry Regulatory Authority (FINRA) Rule 5150]. We find strong evidence that more reputable banks focus on choosing large firms as peers and appear to place more emphasis on product market space. We also find some evidence that banks tend to choose comps with higher valuations after FINRA Rule 5150 is enacted.

Additional analyses reveal that the number of peers chosen by the target's investment bank is negatively related to how unique the target's products are relative to other firms. We also find some evidence, albeit weak, that banks choose peers with higher valuations, which could lead to overpayment, in unsuccessful buyout transactions. Finally, among deals in which target firms hire multiple investment banks, high overlap is evident in peer selection among banks, suggesting that comparable firms are carefully chosen by investment banks.

[2] See, for example, the classic "Valuation" text by Koller, Goedhart, and Wessels (2005), in which the first entry in their list of best practices for the multiples approach to valuation ("multiples" is a synonym for CCA) is "Choose comparables with similar prospects for ROIC (return on invested capital) and growth." The way the authors recommend achieving this best practice is to select peer firms from the focal firm's industry, though they are somewhat reflective about how a practitioner should define "industry."

Overall, the bulk of our evidence is consistent with the notion that target advisors in M&A deals strategically select peer firms in their fairness opinion valuations in a way that increases the perceived value of the target firm, which aids the negotiation of a higher offer price from the acquirer. Our evidence is generally inconsistent with the idea that the peer selection process is colored by an investment bank's desire to make the offered price appear high relative to selected low-valued peers, although we do find some evidence of this incentive in some subsamples, including deals subject to management agency problems, such as management-led buyouts.

A growing literature on peer selection relates to the main idea in this paper. This literature examines the choice of peers in the competitive benchmarking of chief executive officer (CEO) compensation (e.g., Bizjak, Lemmon, and Naveen, 2008; Faulkender and Yang, 2010; Bizjak, Lemmon, and Nguyen 2011; Albuquerque, De Franco, and Verdi, 2013; Cadman and Carter, 2014; De Vaan, Elbers, and DiPrete, 2019). While some disagreement arises in the literature, the broad conclusion is that firms appear to game the benchmarking process by including larger companies with more highly paid CEOs in their peer group, consequently omitting potentially comparable firms that are smaller and have lower-paid CEOs. Most of our results are also consistent with strategic peer selection, but in a very different context.

Our paper contributes to the literature on M&A valuation. The usefulness of investment bank valuations in fairness opinions in M&As has been debated among shareholders, practitioners, legal scholars, and regulators (e.g., DeAngelo, 1986, 1990; Bebchuk and Kahan, 1989; Davidoff, 2006; Kisgen, Qian, and Song, 2009; Holthausen and Zmijewski, 2012; Cain and Denis, 2013; Liu, 2020). Both regulators and courts emphasize that the real informative value of an investment banker's work is in the valuation analysis, not its bottom-line conclusion of whether the offer price is fair.

Yet, one of the prominent valuation methods used by investment banks in their valuation analyses in M&A deals, CCA, has not been extensively studied. In the existing literature, Alford (1992) provides largely descriptive evidence about the use of the price-to-earnings multiple in CCA, and Kaplan and Ruback (1995) use a small sample of transactions to assess the accuracy of the CCA method relative to DCF models of valuation in exactly the same context. Kim and Ritter (1999) examine the use of various types of multiples and CCA in IPOs. Beatty, Riffe, and Thompson (1999) and Officer (2007) focus on CCA in the valuation of private firms, with the latter concluding that, based on CCA, M&A deals for private firms are typically conducted at lower multiples than deals for public firms are. Bhojraj and Lee (2002) is probably the paper most similar to ours in spirit. Its authors discuss the efficacy of the selection process for comparable firms in CCA in terms of predicting future returns and multiples for the focal firm. Our paper aims to contribute to this literature by providing, to our knowledge, the first large-sample evidence on investment bankers' choices of peer firms in CCA. We show that investment banks strategically select peers with higher valuation multiples, which are positively related to deal premiums. These findings add to the broader literature that investigates accounting-based market multiples and peer selection in equity valuation.

Our results also highlight the importance of defining industry boundaries and product market spaces. Although banks selecting peer firms from the same industry to match the risk profile and growth opportunities of the focal firm is uncontroversial, the definition of industry is less straightforward. We find strong evidence that textual-based industry classifications, particularly the product similarity score from Hoberg and Phillips (2010, 2016), have the highest power in explaining the choice of comparable companies compared with measures based on commonly used SIC codes. These results suggest that product market space is among the important factors investment banks consider in peer selection, and our study builds on Hoberg and Phillips's work showing that their novel measure of product similarity, using textual analyses of 10-K filings, is superior to fixed industry measures.

The rest of the paper is organized as follows. Section 2 reviews background information and the setting. In Section 3, we describe our data and sample construction. In Sections 4, 5, and 6, we investigate investment banks' choice of peers in CCA. Section 7 considers the value implications of CCA. Section 8 provides additional analyses and Section 9 concludes.

2. The setting

In this section, we describe the M&A process, including the role of the investment bank or banks in the valuation analysis. We focus on the target firm's perspective because target firms are almost always required to file merger-related documents, which allow us to collect the relevant data.[3] Fig. 1 illustrates a typical timeline of an M&A negotiation process, and Appendix B and Appendix C provide an example of an actual merger, sourced from regulatory filings. The sales process is typically initiated privately when a bidder contacts a target or when the target considers putting itself up for sale. The target hires one or more investment banks at this time, and the banks then prepare financial analyses and identify and negotiate with potential bidders. As part of this process, the bank conducts analyses to determine a valuation range for the target. The valuation estimates are used to negotiate the offer price, and merger terms are formally delivered to the target board as part of the valuation written opinion. Once the deal terms are finalized, the merger is publicly announced and the fairness opinions, which is where we collect the valuation estimates, are disclosed in regulatory filings shortly thereafter.

[3] Most bidders are not required to file proxy statements because bidder shareholder approval is typically not needed to complete an M&A transaction. Bidder shareholder approval is required only if a bidder needs to issue 20% or more new shares to finance the deal. See Michael (1992) for details on the history of corporate governance listing standards in the United States. In Li, Liu, and Wu (2018), see Internet Appendix Table IA1 for more information on listing rules of the NYSE, Amex, and Nasdaq and shareholder approval in M&As. Also see Section III for a more detailed discussion on various M&A filings required by the Security and Exchange Commission.

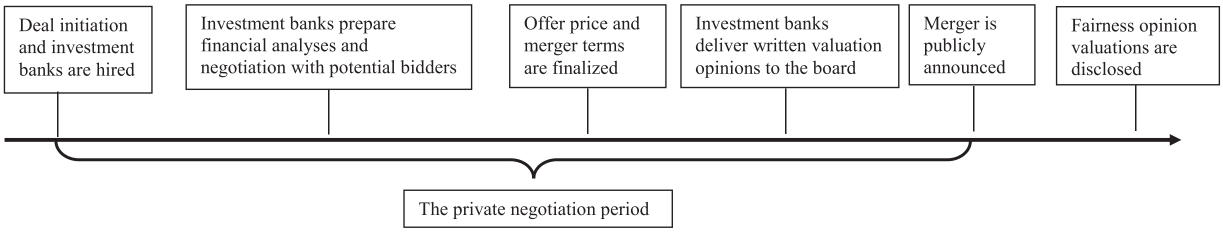

Fig. 1. The timeline of investment bank valuation analysis in the merger and acquisition (M&A) process. This figure illustrates the timeline of a typical valuation analysis provided by investment banks during the M&A negotiation process. See Appendix B for a specific example.

The investment bank typically uses multiple methods to estimate the value of the target firm. The three most common techniques are discounted cash flow analysis, comparable companies (or public company multiple) analysis, and comparable (or precedent) transaction analysis (Liu, 2020).[4] While the discounted cash flow approach is ubiquitous in academic finance courses, the comps-based approaches are just as, if not more, popular with corporate practitioners and their financial advisors (DeAngelo, 1990; Holthausen and Zmijewski, 2012). Indeed, Gompers, Kaplan, and Mukharlyamov (2016) find that comps-based valuation approaches are more important than the DCF approach for PE investors. Our paper focuses on comparable companies analysis, although studying comparable transaction analysis could yield interesting insights. Unfortunately, studying the latter would involve a great deal of additional data collection and is better saved for a separate research study.

Under the comparable companies approach, the bank identifies companies that are closely comparable to the target firm and estimates a valuation multiple, such as enterprise value to earnings before interest, taxes, depreciation, and amortization (EBITDA), for each comparable company. Using these estimates, the bank then assigns a valuation multiples range for the target firm. Finally, the multiples range is used to estimate the value of the target firm. Appendix C illustrates a comparable companies analysis from an actual merger.

As pointed out in Holthausen and Zmijewski (2012), although this valuation model is simple on the surface, the comparable companies approach is a highly involved and complex process. The most important part of this process is the selection of the comparable companies, as they are critical in determining the final valuation estimate. The investment bank faces several incentives, some competing, when valuing the target firm. The investment bank needs to choose peer firms that are reasonablely comparable companies to avoid shareholder litigation and potential damage to reputation.[5] Conditional on that, the banks could have room to choose comps that overestimate or underestimate the target's value.

On the one hand, the bank and its client can overestimate the target value, by selecting peers with higher valuations, to negotiate a higher price with bidding firms. On the other hand, the bank can underestimate target value so that the final sales price looks more attractive for shareholder approval. Concerning the latter, the investment bank valuation process has been criticized a great deal by regulators and legal experts because of banks' fee structure. Bebchuk and Kahan (1989) argue that investment banks are inherently conflicted due to their compensation structure, in which advisory fees are typically contingent on deal completion. This contingent fee structure creates incentives for investment banks to help execute deals by rubber-stamping management proposals.[6] In contrast to legal scholars' dim view of bank valuations due to concerns of conflicts of interests, economists are more optimistic about their worth. This is because banks have their reputation capital at stake, given that they are repeated players in the M&A markets. Empirical studies show that fairness opinion valuations are not driven by conflicts of interest, and the contingent payment fee structure does not affect the quality of banks' advisory services (Rau, 2000; Calomiris and Hitscherich, 2007; Cain and Denis, 2013).

3. Data

This section describe the data used in our analysis.

3.1. Sample construction

Table 1, Panel A, describes our sample selection criteria. We obtain 6,661 M&A deals from 1995 through 2017 after applying standard filters. We hand-collect valuation analysis data from deal regulatory filings, which require that the

[4] Liu (2020) reports that 91.6% of the valuation analyses use discounted cash flow analysis, 90.1% use comparable companies analysis, and 87.7% use comparable transaction analysis in a sample of deals with multiple fairness opinions.

[5] Investment banks and their fairness opinions have been under scrutiny over the years. In *Weinberger v. UOP, Inc.*, 457 A.2d 701 (Del. 1983), minority shareholders alleged that the company's investment banker breached their fiduciary duty by rendering a biased fairness opinion. The vice chancellor concluded that the investment bank did not owe shareholders a fiduciary duty because the bank was retained by the company's management and the relation between the bank and shareholders is characterized as only contractual. However, in *Schneider v. Lazard Frères & Co.*, 552 N.YS.2d 571 (App. Div. 1990), the court held that because the special committee was an agent of the shareholders, the bank, hired by the special committee, was a subagent of the shareholders. As such, the bank inherited the fiduciary duties owed by the directors. *Schneider* marked the first time a bank had been held liable to shareholders (Haire, 2000).

[6] Elson (1992, p. 1002) states: "A suspect fairness opinion adds nothing.... It is as necessary to valuation analysis as is the appendix to the human digestive system."

Table 1
Sample selection and distribution.
This table presents how we form our sample (Panel A) and a temporal distribution of the full sample (Panel B). We draw deals from the 1995 to 2017 time period. We require that target firms be public firms and that deal status be either completed or withdrawn. We also require that the deal value reported by Securities Data Company (SDC) be $1 million or more and that the form of the deal be either merger or acquisition. We further require that bidders seek to purchase 50% or more of target ownership and that the target hires at least one financial advisor. We merge SDC data with the Center for Research in Securities Prices (CRSP) and Compustat data to obtain basic accounting data. We further exclude deals in which the merger documents are unavailable on the Securities and Exchange Commission (SEC) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Finally, we keep the deals that disclose at least one comparable company in the SEC filings. In Panel B, "Year" is the year a deal is announced. "Percent of deals" is the number of deals in the year or industry divided by the total number of deals over the sample period. "Average number of comparable companies" is the average number of the target firm's peer companies selected in the comparable companies analysis. "Minimum number of comparable companies" is the minimum number of the target firm's peer companies selected in the comparable companies analysis. "Maximum number of comparable companies" is the maximum number of the target firm's peer companies selected in the comparable companies analysis.

Panel A: Sample selection

Sample filter	Number of deals
Mergers announced during 1995 to 2017	41,058
Target status: public	11,714
Deal status: completed or withdrawn	10,504
Deal value: $\geq$ $1 million	9,471
Percent of shares acquirer is seeking to purchase $\geq$ 50%	9,418
Number of target financial advisors $\geq$ 1	8,089
Return data available on CRSP and basic accounting data available on Compustat	6,661
Merger documents available on SEC EDGAR	
SEC Form DEFM 14A	2,473
SEC Form S-4	1,718
SEC Form SC 14D9	1,366
Total	5,557
Merger documents contain fairness opinion	
SEC Form DEFM 14A	2,457
SEC Form S-4	1,634
SEC Form SC 14D9	1,226
Total	5,317
Comparable company disclosed in the merger document	
SEC Form DEFM 14A	2,118
SEC Form S-4	1,278
SEC Form SC 14D9	511
Total	3,907

Panel B: Sample distribution

Year	Number of deals	Percent of deals	Average number of comparable companies	Minimum number of comparable companies	Maximum number of comparable companies
1995	90	2.30	8.48	1	34
1996	136	3.47	8.50	1	45
1997	183	4.67	8.64	1	28
1998	233	5.95	8.68	1	39
1999	247	6.31	8.81	2	41
2000	200	5.11	8.70	1	30
2001	175	4.47	9.51	1	41
2002	119	3.04	8.95	1	29
2003	150	3.83	9.53	1	34
2004	161	4.11	9.34	1	27
2005	188	4.80	9.32	1	31
2006	232	5.92	8.69	1	35
2007	255	6.51	8.90	1	34
2008	143	3.65	8.25	1	24
2009	116	2.96	8.72	2	34
2010	180	4.60	8.69	1	28
2011	151	3.85	8.82	1	32
2012	156	3.98	8.58	1	27
2013	146	3.73	9.41	1	31
2014	160	4.08	9.81	1	37
2015	181	4.62	9.39	1	40
2016	176	4.49	9.63	1	27
2017	129	3.29	9.42	2	48
Total	3,907	100%			

target firm files either an SEC Form DEFM 14A for cash offers, an SEC Form SC 14D9 (and its amendment) for tender offers, or a joint SEC Form S-4 (and its amendment) for stock offers. This requirement yields 5,557 deals. To collect information on comparable companies, we further require the deals' M&A filings to include the fairness opinion valuation from the target advisors, which is usually disclosed in the "Opinion of financial advisors" section. We illustrate an example of the comparable companies analysis disclosures in the M&A filings in Appendix B and Appendix C using the example of Schneider Electric SA acquiring BEI Technologies, Inc., in 2005.

Among the 2,473 cash mergers (i.e., DEFM 14A filings), the target boards sought fairness opinions in 2,457 of the deals. Among these deals, we are able to collect information on comparable companies in 2,118 deals (over 86%), confirming the central role this technique plays in M&A valuation analysis. For stock mergers with fairness opinion analysis (i.e., S-4 filings), we can identify comparable companies in over 78% of these deals. We are able to collect information on comparable companies in only less than half of the tender offers (i.e., SC 14D9 filings), because the disclosure of valuation analyses in fairness opinions is required only when firms issue a proxy solicitation to approve the deal. As a target shareholder vote is not required in tender offers, target firms are not required to disclose the valuation analyses in the associated filings. However, target firms still need to disclose whether they have obtained such an opinion.[7] To alleviate concerns that the selective disclosure of valuation analysis in tender offers could affect our results, we include deal fixed effects in all analyses of peer firm selection. Our final sample consists of 3,907 deals from 1995 to 2017.

Among the 3,907 deals, we identify 40,179 peer firm names from the target advisor's comparable companies analysis section. We match the peer firm name with company names in the Compustat database. We have 4,529 unique firm names that cannot be precisely matched by company names. For each of these observations, we match the comparable company name with Compustat company names. We are able to identify 3,137 firms out of the 4,529 unmatched firms.[8] Our final sample consists of 3,907 deals with 35,147 comparable companies with financial information available in the Center for Research in Security Prices (CRSP) and Compustat database. The 35,147 comparable companies represent more than seven thousand unique firms.

Table 1, Panel B, presents the distribution of sample deals by year. Consistent with prior studies (e.g., Andrade, Mitchell and Stafford, 2001; Harford, 2005), we observe a large merger wave in the late 1990s and early 2000s. Also evident is a fairly large number of deals during 2005–2007 due to a leveraged buyout boom (Kaplan and Stromberg, 2009). On average, investment banks choose between eight and ten comparable firms per deal, and this range is stable across our sample period.

3.2. Summary statistics

Panel A of Table 2 presents the summary statistics for the sample deals. See Appendix A for details on the variables analyzed in Table 2 and in subsequent analyses. The mean of deal value is $2.1 billion, and the median is $0.44 billion. Consistent with prior studies, M&A transactions in recent decades are mostly friendly deals with substantial premiums (e.g., Betton, Eckbo, and Thorburn, 2008; Bates and Becher, 2017), as we find that less than 1% of the deals in the sample are classified as hostile by the Securities Data Company (SDC) and the average premium is 44%. Four percent of the deals are withdrawn. Fifteen percent of the deals are buyouts, and 13.2% are tender offers. Seventy-three percent of the deals involve public acquirers, and 44% (26%) of deals use cash (stock) only as the payment method.

4. Industry analysis

We analyze the importance of industry association in comparable companies analysis in this section.

4.1. Descriptive statistics

Panel B of Table 2 shows the percentage of peer firms that have the same industry affiliation as the target firm, using alternative industry classification codes: one-, two-, three-, and four-digit Standard Industrial Classification (SIC) codes and Text-based Network Industry Classifications (TNIC) codes, which derive from the Hoberg and Phillips (2010, 2016) product similarity scores. Hoberg and Phillips estimate product similarity between firms by performing textual analysis of product descriptions on firm 10 K filings.[9]

The results show that the mean likelihood that the target firm industry code matches that from the comparable company ranges from 51% using a four-digit SIC code to 84% using a one-digit SIC code. Further, the product similarity score between the chosen peer and the target firm is around 0.16, which is more than four times higher than that from a randomly selected pseudo peer firm (the last row of Panel B). On the one hand, this analysis suggests that firm industry is a key metric for matching target firms with comparable companies. On the other hand, it is surprising that industry codes are not more important in choosing peers. For example, 49% of peer firms have a different four-digit SIC code than the target. Is industry affiliation an unimportant consideration for peer selection in many deals or is there an alternative explanation?

We consider several possible explanations for why peer-firm industry (SIC) codes frequently differ from target industry codes. First, it is possible that chosen peer firms

[7] See Cain and Denis (2013) and Regulation M-A, 17 C.F.R. Sec. 229.1014(b) (2013), for disclosure requirements in tender offers.

[8] We find that the most common reasons for inconsistency between comparable company names disclosed in the merger filings and Compustat company names are that the merger documents use the abbreviated company names (e.g., IBM) and Compustat reports the full names (i.e., International Business Machines Corp.) or that the merger documents use names before a firm's restructuring (e.g., Google) and Compustat records the parent name (i.e., Alphabet, Inc.).

[9] We thank Professors Gerard Hoberg and Gordon Phillips for making their data publicly available.

Table 2
Summary statistics.
This table presents summary statistics of merger and acquisition (M&A) deals during the sample period 1995 2017. Panel A reports the summary statistics of the main deal characteristics for the full sample. Panel B reports summary statistics of the percent of peer firms that have the same industry affiliation as the target firm, using alternative industry classifications. The second to last row of Panel B reports statistics on the value of the product similarity score between the target firm and actual peer firms. The last row of Panel B reports statistics on the value of the product similarity score between the target firm and randomly selected peer firms. Definitions of all variables are in Appendix A.

Variable	*N*	Mean	Standard deviation	25th percentile	Median	75th percentile
Panel A: Deal characteristics						
Deal Value (millions of dollars)	3,907	2,106.297	4,960.127	138.218	440.691	1,650.540
Buyout	3,907	0.155	0.362	0.000	0.000	0.000
Tender Offer	3,907	0.132	0.339	0.000	0.000	0.000
All Cash	3,907	0.438	0.496	0.000	0.000	1.000
All Stock	3,907	0.260	0.438	0.000	0.000	1.000
Hostile	3,907	0.007	0.083	0.000	0.000	0.000
Public Acquirer	3,907	0.727	0.446	0.000	1.000	1.000
Withdrawn	3,907	0.042	0.202	0.000	0.000	0.000
Premium (-84)	3,757	44.044%	46.489%	18.182%	36.842%	61.414%
CAR (-84, +126)	3,907	32.158%	47.241%	5.912%	25.542%	50.203%
Panel B: Target and peer firm industry affiliation						
Same SIC 1	3,907	0.839	0.276	0.789	1.000	1.000
Same SIC 2	3,907	0.753	0.328	0.556	0.938	1.000
Same SIC 3	3,907	0.641	0.369	0.308	0.778	1.000
Same SIC 4	3,907	0.514	0.376	0.150	0.500	0.900
Same TNIC 2	3,615	0.756	0.278	0.615	0.857	1.000
Same TNIC 3	3,615	0.613	0.344	0.333	0.692	0.923
Product Similarity Score	3,615	0.158	0.072	0.106	0.153	0.202
Product Similarity Score (Random)	3,615	0.038	0.023	0.023	0.033	0.047

could share the same SIC codes as acquirers but not targets, and industry matching could improve when the peer-firm SIC code matches that of either the acquirer or the target. We consider this possibility by forming a subsample of deals in which both targets and bidders are public firms so that we can measure industry affiliation on both sides. We analyze three scenarios, the base case in which peer SIC equals target SIC, the case in which peer SIC equals either target or bidder SIC, and the scenario in which peer SIC does not equal either the bidder or the target's SIC code. We perform this analysis for each SIC code group, from the one-digit SIC code group to the four-digit code group.

Panel A of Table 3 presents results for deals that involve publicly traded targets and bidders. The first row in each industry grouping reports the percentage of observations in that group. The importance of SIC industry classification improves from considering only the target (when one-digit SIC code matching, for example, has a match percentage of 85%) to matching on either the target or the bidder's SIC (when one-digit SIC code matching produces a match for 91% of the sample). Even in the latter case, however, when SIC-code matching appears effective, 9% of peer firms have one-digit SIC codes that do not match either the target's or the acquirer's, and this percentage increases to 25% (37%) when using three-digit SIC codes (four-digit SIC codes).

In Panel B of Table 3, we push further by considering a subsample in which the target and bidder have different SIC codes. Again, considering either the target or the bidder's SIC code, not just the target's, helps, as the percentage of the peers' one-digit (four-digit) SIC codes that matches the targets' industry codes is only 59% (36%) but rises to 85% (54%) when considering either the target or the bidder's SIC code. Still, Column 5 shows that a large percentage of peer SIC codes do not match either the target's or the bidder's, particularly for three-digit (35%) and four-digit (46%) codes.

We next consider whether inaccuracies in SIC codes can understate the importance of industry relatedness in peer selection. We do so by computing the average product similarity score between peers and the target and between peers and the acquirer. If the peer firms with different SIC codes are truly unrelated to the merging parties, we would expect to find an average product similarity score close to the average of random pairs in the Compustat universe, which is 0.038.

Inconsistent with this explanation, these seemingly unrelated peers according to SIC codes have relatively high product similarity with the merging firms, especially with the target firm. For example, Column 3 of Table 3, Panel A, shows that the average product similarity score is 0.10 (peer matched to the bidder) to 0.12 (peer matched to the target) for peers that do not have the same one-digit SIC code as either the target or the acquirer. Those average similarity scores rise to 0.13 with the bidder and 0.15 with the target for peers that do not have the same four-digit SIC code as either the target or the acquirer. Panel B, Column 5, also emphasizes the importance that banks place on matching on industry affiliation, as product similarity scores range from 0.081 to 0.14 despite the fact that the peer, target, and bidder all have different SIC codes.

To provide some texture to this analysis, we offer examples in Panel C of Table 3, in which the peer appears to share similarities in its business profile with the merging firms' business lines, but the peer firm's SIC code, even

Table 3
A closer look at industry affiliation.
This table presents statistics on peer industry affiliation for a sample of strategic deals in which both targets and bidders are public firms. In Panel A, Column 1 represents observations for which peer Standard Industrial Classification (SIC) equals target SIC; Column 2, observations in which peer SIC is equal to either target or bidder SIC; and Column 3, cases in which peer SIC is not equal to either target or bidder SIC. Statistics are presented in four groups, from the SIC one-digit group (SIC 1) to the SIC four-digit group (SIC 4). Each SIC classification code reports three statistics: the percentage of observations from the sample that are in that group, the average product similarity score between the peer and target, and the average product similarity score between the peer and the bidder. Panel B reports similar statistics, but they are grouped by whether the target and bidder have the same or different SIC 1 code, SIC 2 code, etc. Panel B also reports, in the last two rows of each SIC category, the average number of business segments for the target and the bidder. Panel C provides five examples in which peers have a different one-digit SIC code than both the target and the bidder. We obtain business profile information from merger news articles and company Securities and Exchange Commission Form 10-K filings. Panel D reports statistics based on whether a deal involves single business segment firms versus multi-business segment firms. The single-segment group contains deals in which both the target firm and the bidder have only one business segment. The multi-segment group contains deals in which at least one of the merging firms has multiple business segments.

Panel A: Peer industry affiliation for strategic deals

Group	Peer SIC = target SIC	Peer SIC = target or bidder SIC	Peer SIC ≠ target or bidder SIC
	(1)	(2)	(3)
SIC 1	85.25%	90.56%	9.44%
Product similarity (target)	0.172	0.171	0.116
Product similarity (bidder)	0.150	0.150	0.097
SIC 2	77.40%	83.70%	16.30%
Product similarity (target)	0.176	0.173	0.117
Product similarity (bidder)	0.152	0.153	0.101
SIC 3	67.00%	75.03%	24.97%
Product similarity (target)	0.180	0.176	0.130
Product similarity (bidder)	0.155	0.156	0.114
SIC 4	53.27%	62.85%	37.15%
Product similarity (target)	0.184	0.179	0.150
Product similarity (bidder)	0.157	0.159	0.128

Panel B: Subsample analysis based on whether the target firm and the bidder have the same SIC code

Group	Target and bidder have the same SIC code		Target and bidder have different SIC codes		
	Peer SIC = target or bidder SIC (1)	Peer SIC ≠ target or bidder SIC (2)	Peer SIC = target SIC (3)	Peer SIC = target or bidder SIC (4)	Peer SIC ≠ target or bidder SIC (5)
SIC 1	91.88%	8.12%	58.89%	85.32%	14.68%
Product similarity (target)	0.178	0.116	0.144	0.141	0.117
Product similarity (bidder)	0.163	0.103	0.082	0.095	0.081
Number of business segments (target)	1.617	1.824	1.779	1.814	2.030
Number of business segments (bidder)	2.103	2.532	3.345	3.288	3.457
SIC 2	88.48%	11.52%	51.22%	72.41%	27.59%
Product similarity (target)	0.186	0.125	0.147	0.142	0.111
Product similarity (bidder)	0.172	0.113	0.091	0.104	0.084
Number of business segments (target)	1.545	1.707	1.875	1.925	2.056
Number of business segments (bidder)	2.012	2.386	3.154	3.074	3.225
SIC 3	82.11%	17.89%	45.69%	65.06%	34.94%
Product similarity (target)	0.188	0.146	0.168	0.159	0.114
Product similarity (bidder)	0.178	0.136	0.111	0.122	0.091
Number of business segments (target)	1.502	1.588	1.861	1.867	2.053
Number of business segments (bidder)	1.941	2.147	2.912	2.838	3.139
SIC 4	73.16%	26.84%	36.39%	54.11%	45.89%
Product similarity (target)	0.192	0.164	0.175	0.167	0.140
Product similarity (bidder)	0.184	0.152	0.125	0.135	0.112
Number of business segments (target)	1.518	1.520	1.732	1.749	1.828
Number of business segments (bidder)	1.866	2.029	2.751	2.669	2.791

Panel C: Examples of peers with different one-digit SIC codes than bidder and target

Example	Name	SIC	Description
	Target		
Deal 1	Copano Energy	4922	Copano provides comprehensive services to natural gas producers, including natural gas gathering, processing, treating, and liquids fractionation.
Deal 2	National Medical Health Card Systems	6411	The company''s operations include pharmacy benefit management services. It owns a mail service pharmacy and a specialty service pharmacy.
Deal 3	SGX Pharmaceuticals	2836	SGX Pharmaceuticals is a biotechnology company focused on the discovery, development, and commercialization of innovative cancer therapeutics.

(*continued on next page*)

Table 3
(*continued*)

Deal 4	Powerhouse Technologies	7990	The company develops, manufactures, sells, and operates gaming and wagering systems in the on-line lottery, video lottery, and casino gaming and pari-mutuel wagering markets.
Deal 5	PAETEC Holding Corp.	4899	PAETEC provides local and long-distance voice services, data and Internet services, and software applications.
	Bidder		
Deal 1	Kinder Morgan Energy Partners	4922	Kinder Morgan Energy Partners is a leading pipeline transportation and energy storage company. Its pipelines transport natural gas, gasoline, crude oil, CO_2, and other products.
Deal 2	SXC Health Solutions	7372	SXC provides comprehensive pharmacy benefit management systems and services, pharmacy practice management systems, and related prescription fulfillment services.
Deal 3	Eli Lilly & Co	2834	The company discovers, develops, manufactures, and sells pharmaceutical products.
Deal 4	Anchor Gaming	7990	Anchor Gaming is a diversified gaming company that seeks to capitalize on its experience as an operator and developer of gaming machines and casinos by developing gaming-oriented businesses.
Deal 5	Windstream Corp.	4813	Windstream is a customer-focused telecommunications company that provides phone, high-speed Internet, and digital television services.
	Peer		
Deal 1	MarkWest Energy Partners	1311	MarkWest is engaged in the gathering, processing, and transportation of natural gas; the transportation, fractionation, storage, and marketing of natural gas liquids; and the gathering and transportation of crude oil.
Deal 2	CVS Caremark	5912	CVS Caremark's operations are grouped into two businesses: retail pharmacy and pharmacy benefit management.
Deal 3	Exelixis	8731	Exelixis is specialized in developing innovative therapies for cancer and other serious diseases.
Deal 4	Autotote	3578	The company operates in pari-mutuel operations and lottery operations, systems, and equipment sales.
Deal 5	EarthLink, Inc.	7370	EarthLink, Inc., is an Internet service provider, offering nationwide Internet access and related value-added services.

Panel D: Subsample analysis based on deals involving single- versus multi-segment firms

	Single Segment		Multiple Segments	
Group	Peer SIC =target or bidder SIC	Peer SIC ≠target or bidder SIC	Peer SIC = target or bidder SIC	Peer SIC ≠ target or bidder SIC
SIC 1	93.41%	6.59%	87.91%	12.09%
Product similarity (target)	0.196	0.115	0.148	0.117
Product similarity (bidder)	0.180	0.111	0.124	0.089
SIC 2	88.84%	11.16%	78.92%	21.08%
Product similarity (target)	0.197	0.121	0.151	0.117
Product similarity (bidder)	0.182	0.117	0.127	0.092
SIC 3	82.29%	17.71%	68.29%	31.71%
Product similarity (target)	0.200	0.147	0.155	0.120
Product similarity (bidder)	0.184	0.138	0.130	0.098
SIC 4	69.27%	30.73%	56.88%	43.12%
Product similarity (target)	0.202	0.178	0.158	0.127
Product similarity (bidder)	0.187	0.159	0.132	0.102

at the one-digit level, differs from the target's or bidder's. For example, in what we refer to as Deal 1 in the table the peer firm MarkWest Energy Partners has an SIC code of 1311, different than both the target (Copano Energy) and the bidder (Kinder Morgan Energy), which have an SIC code of 4922. By reading merger news articles and company 10-K filings, we find that the businesses of the target firm and peer firm are very similar. The target firm provides comprehensive services to natural gas producers, including natural gas gathering, processing, treating, and liquids fractionation, and the peer firm is engaged in the gathering, processing, and transportation of natural gas. This example, along with the others in that panel, emphasizes how misleading SIC codes, even one-digit codes, can be.

Why are SIC codes not more effective in capturing industry affiliation in peer selection? One possibility is that the accuracy of SIC coding deteriorates as businesses diversify. Compustat assigns SIC codes after an internal process based on reported sales from a firm's business segments (Guenther and Rosman, 1994). Therefore, assigning an SIC code to a single-segment company is relatively straightforward, but assigning SIC codes to multiple-segment firms becomes more complicated and less accurate.

We find evidence consistent with this notion by studying the average number of business segments for each subsample (Table 3, Panel B). For example, when the SIC codes for the target, bidder, and peer all match (Column 1), the target firm and the bidder firm have the least number of business segments. Conversely, the target firm and the bidder firm have the highest number of business segments when the target, bidder, and peer all have different SIC codes (Column 5). For example, target firms' number of business segments ranges from 1.5 to 1.6 in Column 1 and ranges from 1.8 to 2.1 in Column 5. Bidder firms' number of business segments ranges from 1.9 to 2.1 in Column 1 and ranges from 2.8 to 3.5 in Column 5. These differences in number of business segments between Columns 5 and 1 are all statistically significant at the 1% level.

We further separate deals into a single-segment group and a multi-segment group. The single-segment group contains deals in which both the target firm and the bidder have only one business segment. The multi-segment group contains deals in which at least one of the merging firms has multiple business segments. We report the results in Panel D of Table 3. Deals involving multi-segment businesses have a higher percentage of observations for which peer SIC codes do not match either the target's or the bidder's. The percentages of unrelated peers range from 6.6% to 30.7% in the single-segment group compared with 12.1% to 43.1% in the multi-segment group (i.e., approximately one and a half to two times higher in the latter group). Although business segments seem to have an impact on the usefulness of SIC codes in judging the relatedness of firms, even for firms with a single reported segment, the 30.7% of peers that are not related to either the target or the bidder based on four-digit SIC codes is still a nontrivial portion. Yet, the similarity scores for this group (0.18 between peers and the target and 0.16 between peers and the bidder) once again reject the notion that they are unrelated peers. Thus, even for single-segment businesses, refined SIC codes such as three- or four-digit SIC codes appear to underestimate the degree to which related firms operate in the same industry.

4.2. Regression analysis

The preceding descriptive analysis suggests that industry affiliation plays an important role in peer selection, but that the use of SIC codes, particularly three- and four-digit ones, underrepresent this importance. In this section, we conduct a regression analysis to further investigate how industry affiliation affects target advisors' selection from a pool of potential peers (in subsequent sections, we examine how other firm characteristics relate to peer selection). To perform this analysis, we compare the actual chosen comparable company with a benchmark group of peers that could have reasonably been chosen by the target bank but were not. What constitutes a reasonable benchmark group? One could consider a very broad group, such as the entire Compustat universe, but the vast majority of these firms would represent poor potential peers for any one deal. On the other end of the spectrum, one could match on very specific characteristics, such as firm size or growth, but one contribution of our paper is to study how much these characteristics empirically matter in peer selection, instead of assuming their importance. Thus, we desire a benchmark group that is neither too broad nor too narrow.

We therefore match each chosen comparable company with ten randomly selected firms that have the same one-digit SIC code as the target firm. We acknowledge that matching on one-digit SIC codes is imperfect, given the shortcomings of SIC codes. However, our analyses have shown that the more granular SIC codes, such as the three- and four-digits ones, are particularly prone to misrepresenting industry affiliation, but the broader one-digit SIC code performs better, as the average (median) deal has actual chosen peers with the same one-digit SIC code as the target 84% (100%) of the time (see Table 2). Nonetheless, our key results are robust to alternative peer group choices.[10]

The general model we use to assess the importance of industry affiliation and later various firm characteristics on comparable company choice is

$$\Pr(\text{Comp} = 1|\text{X}) = \alpha + \beta' X, \tag{1}$$

where the dependent variable takes the value of one if the peer is chosen as a comparable company in the deal and zero for the matched peer firms that were not chosen and the vector of X variables represent industry or firm characteristics of the peers that the investment bank could consider when choosing the comps. Our regression models also include deal fixed effects to control for unobservable deal characteristics. Because adding a large number of fixed effects to a traditional probit or logit model would induce incidental parameter bias, we follow Lancaster (2000) and Angrist (2001) and use a linear probability model (LPM) to estimate marginal effects.[11]

To assess the importance of industry classification on comparable company choice in a regression setting, we estimate Eq. (1) with the key independent variable being an indicator equal to one if the potential peer has the same industry code as the target firm and zero otherwise for five classification codes (two-, three-, and four-digit SIC codes and two- and three-digit TNIC codes). The product similarity score between the potential peer and the target is a continuous measure. To avoid collinearity problems, we separately estimate the model for each alternative industry measure.

We present estimated slope coefficients and associated t-statistics, in parentheses, in Table 4. We compute the t-statistics with heteroskedastic-robust standard errors that are clustered by deal. We standardize the key explanatory variables so that they are easier to interpret and compare across models. Panel A focuses on the relation between

[10] Our results (reported in Internet Appendix Table IA2) remain robust if we remove the restriction of the same one-digit SIC code. In addition, our results (unreported) remain similar if we match each chosen comparable company with five (instead of ten) randomly selected firms that have the same one-digit SIC code as the target firm or if we include all firms that have the same one-digit SIC code as potential peers. In addition, our results remain robust if we use alternative industry classifications to form the potential pool of peers, including Fama-French 12 or 48 industry classifications or the SIC divisions as in Kahle and Walking (1996).

[11] Nevertheless, in an untabulated analysis, we reestimate our tests based on a logit or probit model and obtain similar inference.

Table 4
Regression analysis of industry affiliation and peer firm selection.
This table presents regression results on the selection of comparable companies based on industry information. Panel A reports full sample results for the target side. Panel B reports results for deals involving public targets and public bidders. The dependent variable is an indicator variable that equals one if a company is selected as a peer company in the comparable companies analysis by the target firm's financial advisor and zero otherwise. Independent variables are alternative industry affiliation measures. *Same Target SIC 2 (Same Bidder SIC 2)* is an indicator variable that equals one if a company has the same two-digit Standard Industrial Classification (SIC) code as the target (bidder). Other same industry variables are defined similarly. To construct the sample for this analysis, we match each selected peer company with ten randomly chosen firms, without replacement for each deal, that have the same one-digit SIC code as the target firm. We use a linear probability model with deal fixed effects in all regressions, and all coefficients are multiplied by one hundred to reflect percentage change. We standardize all the variables (so that their mean is zero and their standard deviation is one) for the ease of interpretation. Definitions of all variables are in Appendix A. We cluster the standard errors at the deal level. Heteroskedasticity-consistent t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable = one if selected as a comparable company					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample regression analysis of target						
Same Target SIC 2	8.234***					
	(53.753)					
Same Target SIC 3		9.880***				
		(59.738)				
Same Target SIC 4			8.918***			
			(59.997)			
Same Target TNIC 2				11.803***		
				(84.436)		
Same Target TNIC 3					11.728***	
					(71.040)	
Product Similarity (Target)						14.163***
						(60.612)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	312,103	312,103	312,103	312,103	312,103	312,103
R-squared	0.065	0.106	0.113	0.148	0.160	0.200
Panel B: Subsample regression analysis controlling for bidder industry affiliation						
Same Target SIC 2	3.049***					
	(6.860)					
Same Bidder SIC 2	6.147***					
	(13.230)					
Same Target SIC 3		6.485***				
		(18.452)				
Same Bidder SIC 3		4.366***				
		(12.135)				
Same Target SIC 4			6.166***			
			(27.151)			
Same Bidder SIC 4			4.036***			
			(16.781)			
Same Target TNIC 2				7.826***		
				(37.867)		
Same Bidder TNIC 2				4.946***		
				(22.551)		
Same Target TNIC 3					8.001***	
					(36.100)	
Same Bidder TNIC 3					4.331***	
					(18.438)	
Product Similarity (Target)						10.076***
						(27.424)
Product Similarity (Bidder)						3.430***
						(9.311)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	192,219	192,219	192,219	192,219	192,219	192,219
R-squared	0.077	0.119	0.126	0.150	0.162	0.191

peers and the target. This analysis confirms the descriptive evidence. Industry classification is an important selection criterion for comparable companies, as banks are significantly more likely to choose comps in the same industry as the target, regardless of the industry measure. Moreover, the TNIC codes and the product similarity score from Hoberg and Phillips (2010, 2016) better explain comparable companies choices than do the SIC codes, and the product similarity score does the best as it has the highest point estimate and R-squared value.

In Table 4, Panel B, we further consider how bidder industry affiliation affects peer selection by including bidder industry measures for a subset of deals involving public acquirers. We find that investment banks are also more likely to choose peers that have the same industry affiliation with the acquirer. But, in terms of economic magni-

Table 5
Target and potential peer characteristics: descriptive statistics.
This table presents summary statistics of firm characteristics for target firms, the selected peer firms, acquirer firms, and a group of control firms. Panel A reports pooled median values of firm characteristics for the target firms (Column 1), the selected peer firms (Column 2), and all unselected firms that have the same one-digit Standard Industrial Classification (SIC) code as the target firm (Column 3). Panel B reports pooled median values of firm characteristics for the target firms (Column 1), the acquirer firms (Column 2), the selected peer firms (Column 3), and all unselected firms that have the same one-digit SIC code as the target firm (Column 4) for strategic deals. The remaining columns in both panels present the tests of differences in medians between the selected peer firms and other groups. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Definitions of all variables are in Appendix A.

Panel A: Median target and peer firm characteristics

	Target firms	Actual peers	Potential peers with the same one-digit SIC code	Test of difference	
Variable	(1)	(2)	(3)	(2) - (1)	(2) - (3)
Total Assets	415.765	1,063.391	355.475	647.627***	707.916***
Market Cap (millions of dollars)	296.997	869.348	207.652	572.351***	661.696***
Enterprise Value	360.213	1,031.391	287.883	671.178***	743.508***
M/B	1.701	2.054	1.724	0.353***	0.330***
Sale Growth	0.081	0.103	0.091	0.022***	0.012***
EBITDA Margin	0.134	0.177	0.139	0.043***	0.038***
EV/EBITDA	9.309	10.148	9.782	0.839***	0.366***
Asset Turnover	0.691	0.618	0.612	-0.073***	0.007***

Panel B: Median target, bidder and peer firm characteristics for strategic deal

	Target firms	Bidder firms	Actual peers	Potential peers with the same one-digit SIC code	Test of difference		
Variable	(1)	(2)	(3)	(4)	(3) - (1)	(3) - (2)	(3) - (4)
Total Assets	460.680	3,782.253	1,076.900	335.824	616.221***	-2,705.353***	741.076***
Market Cap (millions of dollars)	319.114	2,739.961	820.951	191.515	501.837***	-1,919.010***	629.436***
Enterprise Value	393.395	3,472.406	966.006	261.740	572.612***	-2,506.400***	704.266***
M/B	1.839	2.230	2.092	1.708	0.254***	-0.137***	0.384***
Sale Growth	0.106	0.126	0.117	0.095	0.011***	-0.009	0.022***
EBITDA Margin	0.145	0.250	0.195	0.142	0.050***	-0.055***	0.053***
EV/EBITDA	9.879	10.943	10.501	9.744	0.622***	-0.442***	0.757***
Asset Turnover	0.636	0.458	0.545	0.591	-0.091***	0.087***	-0.046***

tude, the industry similarity between target firm and peer firm plays a much bigger role in explaining the choices of comparable companies. For example, the coefficient on the product similarity score between potential peers and the target is almost three times as big as that between potential peers and the bidder (10.1 versus 3.4).

Our industry analysis results build on Hoberg and Phillips' work showing that their industry classification measures are superior to fixed industry measures, such as SIC codes. Hoberg and Phillips reason that their variables, such as the product similarity score, benefit from measuring the degree to which specific firms are similar to their peers and how these relations changes over time, neither of which can be derived from static zero-one membership classifications such as SIC codes. Given that it performs the best, we use the product similarity score in subsequent analysis to measure industry classification.

Overall, although SIC codes provide a convenient and efficient way to classify industries and therefore have been widely used by academics, this categorial approach exaggerates differences across category boundaries, which leaves inaccuracies when dissecting a more nuanced and complex situation, such as in the setting of mergers and acquisitions. A naïve conclusion that almost half of selected peers are not related to the merging firms is clearly unjustified in this situation.

5. Firm characteristics analysis

In this section, we investigate which firm characteristics relate to peer selection by target advisors

5.1. Firm characteristics and peer selection

Prior studies show firm size is among the most important factors in peer selection (Faulkender and Yang, 2010; Bizjak, Lemmon, and Nguyen, 2011; Holthausen and Zmijewski, 2012; Albuquerque, De Franco, and Verdi, 2013). Further, Bhojraj and Lee (2002) examine a more general setting and find that sales growth rates, asset efficiency, and profitability affect peer firm selection. We therefore examine how these firm characteristics affect investment bankers' comparable company selection. We begin by studying summary statistics. Panel A of Table 5 reports median comparisons of firm characteristics for the target firms, actual peers, and potential peers for the full sample. The potential peer group is all firms with the same one-digit SIC code as the target firm. The last two columns report how the actual peer groups differ from the target firms as well as the potential peer group. Panel B adds bidder firm statistics, which restricts the sample to deals involving public bidders.

We find a number of interesting univariate patterns suggesting that investment banks tend to choose comparable companies that are larger and more profitable than not only the target firms but also unchosen peer firms. Further, banks tend to choose comps that have relatively high valuation multiples and sales growth. Only the bidders are larger, more profitable, faster growing, and more valuable. On balance, these univariate results suggest that banks tend to choose relatively strong comparable companies, which can lead to higher target valuation estimates. This initial evidence is consistent with investment banks' premium negotiation incentive.

In considering multivariate evidence, we employ a similar estimation approach as before by estimating the linear probability model in Eq. (1), but this time the independent variables include various firm characteristics in addition to the firm industry measure that seems to best describe peer selection: The product similarity score. We measure each independent variable as the potential peer's value for that characteristic, such as market capitalization, minus the characteristic value for the target firm. Prior studies investigating CEO compensation peer groups show an asymmetric effect of firm characteristics on peer firm selection (e.g., Bizjak, Lemmon, and Nguyen, 2011; Albuquerque, De Franco, and Verdi, 2013). For example, Bizjak, Lemmon, and Nguyen (2011) separately estimate the size effect when the difference in firm size between the potential peer and the firm is positive or negative. The authors find that although the likelihood that a given firm is chosen as a peer declines as the absolute difference in size increases, when firms do choose peers that are different in size, they are more likely to choose larger (and less likely to choose smaller) firms as peers. We therefore follow this literature and separately estimate positive and negative differences in firm characteristics to allow for potential asymmetric effects.

Table 6, Panel A, presents estimated slope coefficients and *t*-statistics, in parentheses, for the full sample analysis, focusing on the target. The results, regardless of specification, show significantly positive estimated coefficients on the positive difference in *Market Cap*, suggesting that if potential peers are larger than the target firm, larger peers are more likely to be selected by investment banks as comparable companies. The coefficients on the negative difference in *Market Cap* are negative and highly significant, suggesting that if potential peers are smaller than the target firm, a larger difference (i.e., a smaller peer) is associated with a significantly lower likelihood of selection. Both sides deliver the same message: Investment banks appear to select relatively large firms as peers in their valuation analysis.

Columns 2 to4 report significantly negative coefficients on both the positive and the negative difference in sales growth, suggesting that investment banks are more likely to choose comparable companies that have sales growth closer to the target. However, this relation is asymmetric, as the estimated coefficients on the negative differences are much lower than those on the positive differences. The results suggest that when banks do choose comps with different sales growth than the target, they are more likely to choose firms with higher sales growth and less likely to choose firms with lower sales growth. Further, investment banks tend to choose peers with high efficiency, as the coefficients on the positive difference in *Asset Turnover* are significantly positive and the coefficients on the negative differences are highly negative. Finally, *EBITDA Margin* does not appear to be a first order consideration, as it does not significantly load on either side of the difference after including the other firm characteristics in the specification (Model 4).

In Table 6, Panel B, we study a subsample of deals with public acquirers and public targets, which allows us to add controls for positive and negative differences in firm characteristics between potential peer firms and acquirer firms, as well as the product similarity score between a potential peer and the acquirer. Though some of the other characteristics are less important in Panel B, we continue to find that investment banks are more likely to select firms larger than the target as peers in their valuation analysis. When we compare the potential peer firms with the acquirer, we find a significantly negative estimated coefficients on the positive difference in *Market Cap*, suggesting that peers larger than the acquirer firm are less likely to be selected by investment banks as comparable companies. The coefficients on the negative difference in *Market Cap* are negative, albeit insignificant. Overall, we find that banks are much less likely to choose peers that are smaller than the target or bigger than the acquirer, suggesting that banks tend to choose peers that are in between the size of the target and the acquirer.

5.2. Firm valuation multiples and peer selection

In investigating whether valuation measures of the chosen companies systematically differ from the unchosen peer firms, we consider two valuation measures: market-to-book (M/B) ratio and enterprise value-to-EBITDA (EV/EBITDA). We employ these two measures because the M/B ratio is a commonly used valuation measure in the academic literature, dating to at least Fama and French (1992), and the EV/EBITDA multiple is perhaps the most popular in practice (Holthausen and Zmijewski, 2012). We employ the same methods and linear probability model used in the preceding analysis, simply augmenting the model with the alternative valuation multiples, while continuing to allow for asymmetric effects. Table 7, Panel A, presents estimated slope coefficients and associated *t*-statistics, in parentheses, for the full sample, focusing on the target side.

Regardless of the valuation multiple and the direction of the difference, the estimated slope coefficients on the valuation measures are significantly negative, suggesting that investment banks are more likely to choose comparable companies that have closer valuation multiples to that of the target. However, this relation is asymmetric, as the estimated coefficients are much lower when the difference between the peer firm and the target firm is negative.[12] This result suggests that when banks do choose comps with valuation multiples different from the target

[12] In unreported tests, we confirm that the difference in coefficients on $|Diff\ (M/B)|^{+}$ and $|Diff\ (M/B)|^{-}$ and the difference in coefficients on $|Diff\ (EV/EBITDA)|^{+}$ and $|Diff\ (EV/EBITDA)|^{-}$ are statistically significant at the 1% level. These results are available upon request.

Table 6
Firm characteristics and peer firm selection.
This table presents regression results on the selection of comparable companies based on industry and firm characteristics. Panel A reports full sample results, which focus on the target side. Panel B reports results for deals involving public targets and public bidders. The dependent variable is an indicator variable that equals one if a company is selected as a peer company in the comparable companies analysis by the target firm's financial advisor(s) and zero otherwise. To construct the sample for this analysis, we match each selected peer company with ten randomly chosen firms, without replacement for each deal, that have the same one-digit Standard Industrial Classification code as the target firm. We use a linear probability model with deal fixed effects in all regressions, and all coefficients are multiplied by one hundred to reflect percentage change. The differenced variables each represent the value of the variable for the potential peer firm minus that for the target or bidder. The plus and minus superscripts on the absolute values of these differenced variables indicate positive or negative differences, respectively. Definitions of all variables are in Appendix A. We winsorize all differences in firm characteristics at the first and 99th percentiles. We cluster the standard errors at the deal level. Heteroskedasticity-consistent t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.
[Insert rule here, spanning width of table.].

Panel A: Full sample regression analysis of target

Variable	Dependent variable = one if selected as a comparable company			
	(1)	(2)	(3)	(4)
Product Similarity (Target)	13.713***	13.671***	13.684***	13.694***
	(61.554)	(61.271)	(61.722)	(61.214)
|Diff (Market Cap)| $^+$	0.311***	0.283***	0.357***	0.348***
	(4.237)	(3.863)	(4.880)	(4.755)
|Diff (Market Cap)| $^-$	-3.856***	-3.804***	-3.849***	-3.842***
	(-60.855)	(-59.066)	(-60.219)	(-58.765)
|Diff (Sale Growth)| $^+$		-1.118***	-0.453***	-0.441***
		(-10.926)	(-4.405)	(-4.447)
|Diff (Sale Growth)| $^-$		-2.175***	-1.099***	-1.089***
		(-7.807)	(-3.782)	(-3.766)
|Diff (Asset Turnover)| $^+$			0.567***	0.564***
			(4.230)	(4.213)
|Diff (Asset Turnover)| $^-$			-7.477***	-7.469***
			(-20.428)	(-18.965)
|Diff (EBITDA Margin)| $^+$				0.406
				(0.721)
|Diff (EBITDA Margin)| $^-$				-0.018
				(-0.428)
Constant	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes
Number of observations	312,103	312,103	312,103	312,103
R-squared	0.227	0.227	0.232	0.232

Panel B: Subsample regression analysis controlling for bidder firm characteristics

Variable	Dependent variable = one if selected as a comparable company
Difference relative to target	
Product Similarity (Target)	10.068***
	(28.924)
|Diff (Market Cap)| $^+$	0.938*
	(1.855)
|Diff (Market Cap)| $^-$	-3.765***
	(-7.283)
|Diff (Sale Growth)| $^+$	0.043
	(0.047)
|Diff (Sale Growth)| $^-$	-1.621*
	(-1.889)
|Diff (Asset Turnover)| $^+$	-3.559***
	(-3.198)
|Diff (Asset Turnover)| $^-$	-2.474**
	(-2.208)
|Diff (EBITDA Margin)| $^+$	0.798
	(0.766)
|Diff (EBITDA Margin)| $^-$	-0.994**
	(-2.433)
Difference relative to bidder	
Product Similarity (Bidder)	2.955***
	(8.619)
|Diff (Market Cap)| $^+$	-1.638***
	(-3.082)
|Diff (Market Cap)| $^-$	-0.153
	(-0.306)
|Diff (Sale Growth)| $^+$	-0.247
	(-0.279)
|Diff (Sale Growth)| $^-$	0.592

(*continued on next page*)

Table 6
(*continued*)

	(0.682)
|Diff (Asset Turnover)| $^{+}$	4.436***
	(3.941)
|Diff (Asset Turnover)| $^{-}$	-6.864***
	(-6.173)
|Diff (EBITDA Margin)| $^{+}$	-0.214
	(-0.175)
|Diff (EBITDA Margin)| $^{-}$	1.256***
	(2.831)
Constant	Yes
Deal fixed effects	Yes
Number of observations	192,219
R-squared	0.227

firm, they are more likely to choose firms with higher valuation multiples and less likely to choose firms with lower valuation multiples.

In Table 7 Panel B, we study strategic deals (with publicly traded acquirers and targets) and add controls for differences in valuation measures and firm characteristics between potential peers and acquirer firms, as well as the product similarity score between the potential peer and the acquirer. We continue to find that investment banks are more likely to choose firms with higher valuation multiples and less likely to choose firms with lower valuation multiples, relative to target firms. Comparing the valuation multiples between potential peer firms and the acquirer, banks, in general, tend to select peers that have higher valuations than the acquirer.

Overall, results reported in Table 5, 6 and 7 indicate that when selecting peers in comparable companies analysis, product market space is amongst the important factors investment banks consider. Further, banks tend to strategically select peer firms that are large firms with relatively high valuation multiples. This evidence is more consistent with banks boosting the target firm's value by selecting peers with high valuations to negotiate a higher offer price and is less consistent with banks rubber-stamping the offer price to facilitate deal completion.

6. Cross sectional differences in the determinants of comparable company composition

In this section, we consider whether investment banks' peer selection systematically differs for an important deal type: buyout deals. Buyouts can engender severe managerial conflicts of interest, as target management in buyout deals is often aligned with the buyer and management's interests are likely to diverge from those of the target shareholders. Though managers have a fiduciary duty to negotiate the highest price possible for their shareholders, they also have incentives as purchasers to pay the lowest price possible.

Empirical evidence suggests that target managers do engage in activities that depress stock prices and lower acquisition costs in buyout deals. For example, Perry and Williams (1994) find evidence that management manipulates accounting accruals to reduce reported earnings. Hafzalla (2009) provide evidence that managers selectively release negative disclosures to denigrate their firm just before a buyout transaction. Furthermore, Bargeron, Schlingemann, Stulz, and Zutter (2008) and Officer, Ozbas, and Sensoy (2010) find that target shareholders receive significantly lower premiums in buyout deals. Motivated by the above literature, we examine whether investment banks' peer selection is influenced by managerial incentives in buyout deals.

We partition our sample into buyout and non-buyout subsamples and estimate peer selection for each subsample separately in Table 8. As with the previous analysis, we estimate Eq. (1) using a linear probability model. We also test differences in coefficients between subsamples and report *p*-values in Columns 3 and 6. Panel A presents results using the full sample, focusing on the target. The coefficients on the negative difference in valuation ratios are significantly higher in buyout deals compared with non-buyout deals (-0.100 versus -0.583 for *|Diff (M/B)|*$^{-}$ and -0.137 versus -0.229 for *|Diff (EV/EBITDA)|*$^{-}$), suggesting that investment banks are more likely to select peers with lower valuation ratios in buyout deals compared with non-buyout deals. Also, the coefficients on the positive differences in the valuation ratio are significantly lower in buyout deals compared with non-buyout deals, suggesting that when peers have higher valuation than the target firm, investment banks are less likely to select peers with higher valuation ratios in buyout deals. Regarding other characteristics, investment banks are more likely to choose peers with similar products, smaller size, and lower asset efficiency in buyout deals.

In Table 8, Panel B, we add bidder characteristics, which restricts the sample to deals with public acquirers. For this subsample, bankers look for higher valuations in strategic (i.e., non-buyout) deals, and they look for lower valuations in buyout transactions only with the M/B multiple (and not with the EV/EBITDA multiple).

In Table 8, Panel C, we further compare buyouts to all-cash strategic deals, as buyouts are almost always all-cash deals. This analysis is similar to the one in Panel B of Table 8, except that the analysis in Panel C is restricted to all-cash deals. The key findings are largely unchanged with the focus on all-cash deals. As in Panel B, the loadings on EV/EBITDA are not significantly different for the buyout sample versus the all-cash non-buyout deals. However, if anything, the results for the differences in M/B are stronger for all-cash deals, as both the positive side and the negative side are significantly different at the 10% level or bet-

Table 7
Valuation multiples and peer firm selection.
This table presents regression results on the selection of comparable companies based on industry, firm characteristics, and valuation multiples. Panel A reports full sample results, focusing on the target side. Panel B reports results for deals involving public targets and public bidders. The dependent is an indicator variable that equals one if a company is selected as a peer company in the comparable companies analysis by the target firm's financial advisor(s) and zero otherwise. The regression model estimated for Panel B includes product similarity scores and differences in other bidder and target characteristics (shown in Panel B, Table 6), but we do not report their estimated coefficients for brevity. To construct the sample for this analysis, we match each selected peer company with ten randomly chosen firms, without replacement for each deal, that have the same one-digit Standard Industrial Classification code as the target firm. We use a linear probability model with deal fixed effects in all regressions, and all coefficients are multiplied by one hundred to reflect percentage change. The differenced variables each represent the value of the variable for the potential peer firm minus that for the target or bidder. The plus and minus superscripts on the absolute values of these differenced variables indicate positive or negative differences, respectively. Definitions of all variables are in Appendix A. We winsorize all differences in firm characteristics at the first and 99th percentiles. We cluster the standard errors at the deal level. Heteroskedasticity-consistent *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable	Dependent variable = one if selected as a comparable company	
	(1)	(2)
Panel A: Full sample regression analysis of target		
|Diff (M/B)|$^+$	-0.113***	
	(-6.777)	
|Diff (M/B)|$^-$	-0.503***	
	(-6.133)	
|Diff (EV/EBITDA)|$^+$		-0.033***
		(-10.923)
|Diff (EV/EBITDA)|$^-$		-0.221***
		(-11.747)
Product Similarity (Target)	13.648***	14.056***
	(60.676)	(52.050)
|Diff (Market Cap)| $^+$	0.348***	0.237***
	(4.730)	(2.670)
|Diff (Market Cap)| $^-$	-3.783***	-4.517***
	(-58.520)	(-53.222)
|Diff (Sale Growth)| $^+$	-0.413***	-0.588***
	(-4.182)	(-4.247)
|Diff (Sale Growth)| $^-$	-0.953***	-1.161**
	(-3.280)	(-2.362)
|Diff (Asset Turnover)| $^+$	0.625***	0.377**
	(4.560)	(2.309)
|Diff (Asset Turnover)| $^-$	-7.438***	-8.189***
	(-18.854)	(-15.756)
|Diff (EBITDA Margin)| $^+$	0.529	-1.729**
	(0.935)	(-2.456)
|Diff (EBITDA Margin)| $^-$	-0.016	0.702***
	(-0.369)	(7.228)
Constant	Yes	Yes
Deal fixed effects	Yes	Yes
Number of observations	312,103	227,297
R-squared	0.233	0.240
Panel B: Subsample regression analysis controlling for bidder characteristics		
Difference relative to target		
|Diff (M/B)|$^+$	-0.095	
	(-0.843)	
|Diff (M/B)|$^-$	-0.597***	
	(-4.588)	
Difference relative to bidder		
|Diff (M/B)|$^+$	0.011	
	(0.108)	
|Diff (M/B)|$^-$	-0.131	
	(-0.953)	
Difference relative to target		
|Diff (EV/EBITDA)|$^+$		-0.088***
		(-3.069)
|Diff (EV/EBITDA)|$^-$		-0.191***
		(-5.695)
Difference relative to bidder		
|Diff (EV/EBITDA)|$^+$		0.063**
		(2.227)
|Diff (EV/EBITDA)|$^-$		-0.176***
		(-4.707)
Target and bidder difference characteristics	Yes	Yes
Constant	Yes	Yes
Deal fixed effects	Yes	Yes
Number of observations	192,219	134,819
R-squared	0.228	0.233

Table 8
Peer firm selection in buyout versus non-buyout deals.
This table presents regression results on peer selection in buyouts versus non-buyout deals. Panel A reports full sample results, focusing on the target side. Panel B reports results for deals involving public targets and public bidders, and Panel C presents analysis similar to Panel B, except that Panel C restricts the sample to all-cash deals. The dependent variable is an indicator variable that equals one if a company is selected as a peer company in the comparable companies analysis by the target firm's financial advisor(s). The regression model estimated for Panels B and C includes product similarity scores and differences in other bidder and target characteristics (shown in Panel B, Table 6), but we do not report their estimated coefficients for brevity. To construct the sample for this analysis, we match each selected peer company with ten randomly chosen firms that have the same one-digit Standard Industrial Classification code as the target firm. We use a linear probability model with deal fixed effects in all regressions, and all coefficients are multiplied by one hundred to reflect percentage change. The differenced variables each represent the value of the variable for the potential peer firm minus that for the target or bidder. The plus and minus superscripts on the absolute values of these differenced variables indicate positive or negative differences, respectively. We also test differences in coefficients between buyout and non-buyout deals and report p-values in Columns 3 and 6. Definitions of all variables are in Appendix A. We winsorize all differences in firm characteristics at the first and 99th percentiles. We cluster the standard errors at the deal level. Heteroskedasticity-consistent t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable	M/B Multiple			EV/EBITDA Multiple		
	Buyout	Non-buyout	p-value	Buyout	Non-buyout	p-value
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Target side analysis of buyouts versus all other deals						
|Diff (M/B)|$^+$	-0.199***	-0.097***	0.014			
	(-5.315)	(-5.213)				
|Diff (M/B)|$^-$	-0.100	-0.583***	0.030			
	(-0.487)	(-6.540)				
|Diff (EV/EBITDA)|$^+$				-0.063***	-0.028***	<0.001
				(-9.357)	(-8.428)	
|Diff (EV/EBITDA)|$^-$				-0.137***	-0.229***	0.076
				(-2.883)	(-11.333)	
Product Similarity (Target)	19.984***	13.005***	<0.001	22.110***	13.247***	<0.001
	(33.441)	(56.741)		(36.568)	(48.808)	
|Diff (Market Cap)| $^+$	0.586***	0.281***	0.103	0.355*	0.160	0.362
	(3.465)	(3.409)		(1.866)	(1.590)	
|Diff (Market Cap)| $^-$	-2.819***	-3.921***	<0.001	-3.027***	-4.736***	<0.001
	(-23.402)	(-55.401)		(-20.045)	(-51.449)	
|Diff (Sale Growth)| $^+$	-1.214***	-0.309***	<0.001	-1.516***	-0.497***	0.013
	(-5.486)	(-2.871)		(-3.953)	(-3.361)	
|Diff (Sale Growth)| $^-$	-0.166	-1.084***	0.357	0.271	-1.411***	0.267
	(-0.173)	(-3.538)		(0.189)	(-2.720)	
|Diff (Asset Turnover)| $^+$	-0.452	0.824***	0.001	-0.838**	0.674***	<0.001
	(-1.328)	(5.631)		(-2.342)	(3.753)	
|Diff (Asset Turnover)| $^-$	-3.972***	-8.173***	<0.001	-3.063***	-9.431***	<0.001
	(-4.952)	(-18.459)		(-3.373)	(-15.654)	
|Diff (EBITDA Margin)| $^+$	-3.707	0.605	0.103	-8.569***	-1.167	<0.001
	(-1.429)	(1.051)		(-4.350)	(-1.566)	
|Diff (EBITDA Margin)| $^-$	-0.088	0.004	0.431	0.221	0.751***	0.012
	(-0.821)	(0.077)		(1.214)	(6.983)	
Constant	Yes	Yes		Yes	Yes	
Deal fixed effects	Yes	Yes		Yes	Yes	
Number of observations	50,226	261,877		38,900	188,397	
R-squared	0.273	0.231		0.296	0.237	
Panel B: Buyout deals versus deals with publicly traded targets and bidders						
Difference relative to target						
|Diff (M/B)|$^+$	-0.199***	-0.095	0.375			
	(-5.315)	(-0.843)				
|Diff (M/B)|$^-$	-0.100	-0.597***	0.039			
	(-0.487)	(-4.588)				
Difference relative to bidder						
|Diff (M/B)|$^+$		0.011				
		(0.108)				
|Diff (M/B)|$^-$		-0.131				
		(-0.953)				
Difference relative to target						
|Diff (EV/EBITDA)|$^+$				-0.063***	-0.088***	0.392
				(-9.357)	(-3.069)	
|Diff (EV/EBITDA)|$^-$				-0.137***	-0.191***	0.323
				(-2.883)	(-5.695)	
Difference relative to bidder						
|Diff (EV/EBITDA)|$^+$					0.063**	
					(2.227)	
|Diff (EV/EBITDA)|$^-$					-0.176***	

(*continued on next page*)

Table 8 (*continued*)

Variable	M/B Multiple			EV/EBITDA Multiple		
	Buyout	Non-buyout	*p*-value	Buyout	Non-buyout	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)
					(-4.707)	
Target and bidder difference characteristics	Yes	Yes		Yes	Yes	
Constant	Yes	Yes		Yes	Yes	
Deal fixed effects	Yes	Yes		Yes	Yes	
Number of observations	50,226	192,219		38,900	134,819	
R-squared	0.273	0.228		0.296	0.233	
Panel C: Buyout deals versus all cash deals with publicly traded targets and bidders						
Difference relative to target						
$\lvert Diff\ (M/B)\rvert^{+}$	-0.199***	0.142	0.093			
	(-5.315)	(0.705)				
$\lvert Diff\ (M/B)\rvert^{-}$	-0.100	-0.789***	0.027			
	(-0.487)	(-3.342)				
Difference relative to bidder						
$\lvert Diff\ (M/B)\rvert^{+}$		-0.230				
		(-1.334)				
$\lvert Diff\ (M/B)\rvert^{-}$		0.483*				
		(1.958)				
Difference relative to target						
$\lvert Diff\ (EV/EBITDA)\rvert^{+}$				-0.063***	-0.084	0.746
				(-9.357)	(-1.262)	
$\lvert Diff\ (EV/EBITDA)\rvert^{-}$				-0.137***	-0.144**	0.927
				(-2.883)	(-2.407)	
Difference relative to bidder						
$\lvert Diff\ (EV/EBITDA)\rvert^{+}$					0.054	
					(0.801)	
$\lvert Diff\ (EV/EBITDA)\rvert^{-}$					-0.162**	
					(-1.966)	
Target and bidder difference characteristics	Yes	Yes		Yes	Yes	
Constant	Yes	Yes		Yes	Yes	
Deal fixed effects	Yes	Yes		Yes	Yes	
Number of observations	50,226	52,825		38,900	35,190	
R-squared	0.273	0.260		0.296	0.275	

ter for buyout versus non-buyout deals (only the negative side is significantly different in Panel B).

Overall, the results reported in Table 8 provide some evidence that managerial conflicts of interest appear to affect investment banks' peer selection choices, as peers selected in buyout deals tend to have lower valuation ratios and weaker operating performance, which is consistent with the notion that investment banks strategically select low-value peers to justify the lower premiums offered in buyout deals. However, we acknowledge that we cannot reach a definitive conclusion because of the weaker evidence once controls are included for bidder characteristics.

7. The value implications of comparable companies analysis deal–level analysis

We next conduct a deal-level analysis to investigate potential value implications of peer selection in the comparable companies analysis, and we ask can the comparable companies analysis impact the value received by target shareholders? To perform this analysis, we examine the relation between characteristics of the chosen comparable companies and deal outcomes using the model

$$\text{Deal Outcome}_i = \alpha + \beta' \text{Characteristic Differences}_i + \gamma' \text{Controls}_{\,i} + \varepsilon_i, \qquad (2)$$

where the dependent variable represents either each deal's premium, measured as the offer price relative to the price four months prior to deal announcement, or target cumulative abnormal returns (CARs), measured from four months before to six months after deal announcement.[13] The key independent variables are differences in characteristics, such as market cap, in which each characteristic value from the target firm is subtracted from the mean value across the chosen comparable companies. The controls include target and deal characteristics, as well as industry and year fixed effects. The variables in this model are at the deal level.

We report estimated slope coefficients and robust *t*-statistics, in parentheses, in Table 9. Several characteristics are positively related to deal outcomes. Higher valuation multiples are generally positively correlated with deal premiums and target CARs. For example, a one standard deviation increase in the difference in M/B ratio between peers and the target firm (2.9) is associated with a higher

[13] Eaton, Liu, and Officer (2021) provide evidence that, on average, target stock price runup starts as early as four months prior to the M&A announcement. Our results remain robust if we use a five-month window, or if we follow Schwert (1996, 2000) and use a three-month or two-month pre-event window to calculate premiums and CARs.

Table 9
Peer firm selection and takeover premiums.
This table presents results on how the selection of comparable companies are related to deal premiums. For Columns 1 and 2, the dependent variable is *Premium (-84)*, measured as the offer price from Securities Data Company (SDC) relative to target stock price 84 trading days prior to the merger announcement. For Columns 3 and 4, the dependent variable is *CAR (-84, +126)*, which is the target cumulative abnormal returns (CARs) over the event window (-84, +126), where day 0 is the merger announcement date. The differenced variables each represent the mean value of the variable for the chosen comparable companies minus that for the value for the target firm. For example, for each merger and acquisition deal, *Diff (M/B)* is calculated as the average market-to-book (M/B) ratio among the chosen comparable companies minus the target firm's M/B ratio. Dependent variables are multiplied by one hundred to reflect percentage change. Heteroskedasticity-consistent *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable	Premium (-84)		CAR (-84, +126)	
	(1)	(2)	(3)	(4)
Diff (M/B)	0.840**		0.724**	
	(2.566)		(2.201)	
Diff (EV/EBITDA)		0.043		0.088*
		(0.918)		(1.820)
Product Similarity (Target)	25.165*	27.896**	19.176	20.281
	(1.806)	(2.135)	(1.420)	(1.622)
Diff (Market Cap)	2.634***	2.320***	3.266***	3.135***
	(2.935)	(2.702)	(3.651)	(3.626)
Diff (Sale Growth)	0.453	5.263**	3.912*	6.821**
	(0.172)	(1.962)	(1.672)	(2.541)
Diff (Asset Turnover)	-2.722	2.066	-3.808*	2.409
	(-1.304)	(1.048)	(-1.928)	(1.259)
Diff (EBITDA Margin)	-0.625	14.317*	2.815	30.025***
	(-0.159)	(1.760)	(0.779)	(3.476)
Withdrawn			-34.134***	-30.238***
			(-8.575)	(-8.232)
Target Log (Market Cap)	-2.761***	-2.389***	-1.525**	-1.408**
	(-4.387)	(-3.942)	(-2.565)	(-2.413)
Tender Offer	4.777**	1.755	7.702***	4.810**
	(2.072)	(0.799)	(3.291)	(2.084)
Buyout	-10.750***	-9.854***	-9.845***	-9.783***
	(-5.873)	(-5.428)	(-5.505)	(-5.447)
All Cash	0.447	0.170	0.232	-0.640
	(0.234)	(0.096)	(0.125)	(-0.360)
All Stock	-2.653	-2.419	-5.232**	-2.840
	(-1.168)	(-1.135)	(-2.230)	(-1.260)
Hostile	11.614	6.323	21.381*	18.461
	(0.888)	(0.593)	(1.704)	(1.634)
Product Similarity (Bidder & Target)	1.522	1.286	-1.014	-3.043
	(0.175)	(0.157)	(-0.112)	(-0.345)
Multiple Bidder	9.015***	4.303	7.867**	2.586
	(2.908)	(1.572)	(2.446)	(0.880)
Toehold	-4.834	-2.406	-6.979*	-4.711
	(-1.146)	(-0.608)	(-1.870)	(-1.284)
Log (Number MA Peer)	0.293	-0.253	0.472	0.997
	(0.206)	(-0.191)	(0.329)	(0.740)
Top 8 Advisor	2.304	1.231	1.192	1.345
	(1.432)	(0.828)	(0.736)	(0.861)
Industry and year fixed effects	Yes	Yes	Yes	Yes
Number of observations	3,370	2,857	3,493	2,948
R-squared	0.104	0.113	0.134	0.170

premium of 2.4% (Column 1) and a higher abnormal return of 2.1% (Column 3).[14] The other notable finding is the consistently strong peer size effect. Although target size itself is negatively related to deal premiums, which is consistent with prior literature (e.g., Officer, 2003), the relative size of comparable companies is statistically positively related to deal premiums. A one standard deviation increase in difference in size between peers and target firms (1.16) is associated with a 3.1% increase in premium (Column 1) and 3.8% increase in abnormal returns (Column 3). Also, peers with relatively high sales growth tend to garner larger premiums for target shareholders. Further, higher product similarity scores are generally positively correlated with deal premiums and target CARs.[15] Overall, these results are consistent with the notion that target investment

[14] Similarly, a one standard deviation increase in the difference in EV/EBITDA ratio (20.7) is associated with a higher premium of 0.9% (although not statistically significant) and a higher abnormal return of 1.8% (statistically significant at the 10% level).

[15] The signs of the coefficients of other control variables are largely consistent with prior studies. Huang and Walkling (1987), Schwert (1996), Moeller, Schlingemann, and Stulz (2004), and Offenberg and Pirinsky (2015) show that the takeover premiums are higher in tender offers. Bargeron, Schlingemann, Stulz, and Zutter (2008) and Officer, Ozbas, and Sensoy (2010) report lower premiums in buyout deals.

banks choose more attractive comps to negotiate higher prices for the target.

We suggest caution in interpreting our premium results as our analyses examine associations, not causal relations. For example, reverse causality is a concern as the offer price could largely be known before the peer firms are chosen for comparable companies analysis. We attempt to address any reverse causality concerns by omitting bidder-initiated deals, as the offer price is more likely to be known in advance by the target's advisor in such deals. In untabulated results, we find that the difference in M/B between peers and the target, but not the difference in EV/EBITDA, continues to have a significantly positive relation with deal premiums and target announcement returns after we exclude bidder-initiated deals from the analysis.[16]

Even for non-bidder-initiated deals, however, the peer selection we observe in our sample is obtained from fairness opinions, which are typically written after the deal is finalized. Thus, our analysis in Table 9 relies on the assumption that, in non-bidder-initiated deals, the target bank chooses peer firms early in the sale process (before the offer price is known) and the peer firm composition is not substantially altered for the fairness opinion analysis.[17]

8. Additional analyses

We conduct additional analyses in this section.

8.1. Number of peers chosen in CCA

Table 1, Panel B, shows that although the average number of peers chosen per deal is stable across our sample period, some variation exists. The maximum number of peers is 48 (in 2017) and the minimum number of peers is one (in most years). In this section, we examine factors that can impact the number of peers that banks choose to include in their valuation analysis.

Our main focus is the uniqueness of the target firm relative to its competitors. The intuition is that if a target firm sells products that are very similar compared with its competitors, then banks could have many comparable firms to select as peers. Conversely, a target firm that produces unique products could have fewer firms that banks view as truly comparable. To perform this analysis, we construct our main independent variable, *Target Uniqueness*, defined as one minus the average of the product similarity scores between the target firm and each of its ten closest rivals. The closest rivals are the ten firms having the highest product similarity scores with the target firm. To estimate the effects, we regress a variable that measures the number of comps selected for each deal on *Target Uniqueness*, while controlling for target firm characteristics and deal characteristics.

We present estimated results in the Internet Appendix Table IA3. Consistent with our expectation, we find a significant negative relation between target uniqueness and the number of peers selected in CCA. Economically, a one standard deviation increase in *Target Uniqueness* is associated with 0.7 fewer peer firms selected. Also, target size is positively related to the number of selected peers, and product similarity between the target and the bidder is negatively related to the number of selected peers. We also control for *Acquirer Uniqueness*, which is defined in a similar way as *Target Uniqueness*, and we find that *Acquirer Uniqueness* does not significantly affect the number of selected peers.

8.2. Investment bank reputation

Theoretical studies view investment banks as information-producing intermediaries in the context of financial market transactions such as M&As (e.g., Chemmanur and Fulghieri, 1994; Pichler and Wilhelm, 2001). Although early empirical studies fail to find that investment bank reputation generates positive outcomes (e.g., Bowers and Miller, 1990; Michel, Shaked, and Lee, 1991; Servaes and Zenner, 1996; Rau, 2000), more recent studies report that firms do benefit by hiring more reputable banks in M&As (e.g., Bao and Edmans, 2011; Golubov, Petmezas, and Travlos, 2012.) In addition, Cain and Denis (2013) show that top-tier advisors produce lower absolute valuation errors than lower-tier advisors. Motivated by this literature, we investigate whether bank reputation has a significant impact on the selection of comparable companies.

We construct a reputation measure based on the number of times the bank was hired for an M&A deal, as measured by the number of times the bank performs a fairness opinion and uses the CCA technique. For each year, we rank investment banks based on the number of fairness opinions with CCAs in a five-year rolling window. To accurately measure the number of times each bank was hired, we track mergers between investment banks during our sample period (see Internet Appendix, Fig. IA1). If Bank A acquires Bank B in year *t*, we compute the number of fairness opinions issued by each bank separately before year *t*, and we compute the combined number of fairness opinions after year *t* to rank advisors.[18]

In the spirit of Fang (2005) and Golubov, Petmezas, and Travlos (2012), we classify the top eight investment banks as top tier and all other financial advisors as non–top tier.[19] Our measure, based on a rolling five-year win-

[16] This analysis uses a subsample with deal initiation data from Eaton, Liu, and Officer (2021).

[17] Also see the practitioner-oriented article referred to in footnote 1.

[18] For example, in the case of Merrill Lynch acquiring Advest in 2005, we compute rankings for Advest and Merrill Lynch separately prior to 2005. After the merger, we assign Advest's fairness opinions to Merrill Lynch and rank both Advest and Merrill Lynch based on their combined number of fairness opinions. Our results remain robust if we rank investment banks by their market share or the number of deals they advise.

[19] Fang (2005) argues that the binary classification is preferred over a continuous measure for two reasons. Economically, it captures the two-tiered structure in the investment banking industry of Wall Street. Econometrically, the use of a continuous measure assumes that the variable captures reputation in precision, and it has a constant effect on the dependent variable, while the binary classification enables a better inference on the qualitative difference between more reputable and less reputable banks. As a robustness check, we use top five or top ten as alternative cutoffs for top-tier advisors and obtain similar results.

dow, allows reputations to change and for new top-tier banks to emerge. Internet Appendix Table IA1 lists financial advisors that have been ranked as top advisors at least once during our sample period from 1995 to 2017.

Internet Appendix Table IA4 compares peer selection for the top eight banks versus the non–top eight banks. The most notable finding is that top-tier banks focus on choosing large firms as peers. In fact, the size effect we observe in Table 6 (i.e., the significantly positive coefficients on the positive difference and significantly negative coefficients on the negative difference in *Market Cap*) is entirely driven by top-tier banks. Among non-top-tier banks, we find significantly negative coefficients on both the positive and the negative difference in *Market Cap*, suggesting that non-top banks are more likely to choose comparable companies that are closer in size to targets. However, this relation is asymmetric, suggesting that when non-top banks do choose comps with a different size, they are more likely to choose firms with a larger size and less likely to choose firms with a smaller size.

Also, top-tier banks tend to focus more on product market space, as they are significantly more likely to choose comps with higher product similarity. The results on the interaction of bank reputation and comps' valuation multiples are mixed. The coefficient on the positive difference in M/B ratio is smaller among top banks compared with non-top banks, suggesting that top-tier banks choose comps with higher market valuations. However, this result is not robust because the coefficients are not statistically different if we use the EV/EBITDA multiple as an alternative valuation measure.

8.3. Effects of FINRA rule 5150

In investigating whether investment banks respond to a regulatory change designed to mitigate conflicts of interest, we examine whether investment banks' selection of comps differs following the implementation of FINRA Rule 5150. One principal criticism regarding bank valuation is that conflicts of interest could arise because valuation is usually rendered by the same financial advisor that arranges the merger and collects fees contingent on deal completion. In addition, if a financial advisor has had a prior business relation with target management, this advisor could have an incentive to agree with management's assessment of a transaction. To address these conflicts of interest, in October 2007, the SEC approved Rule 2290, which has been superseded by FINRA Rule 5150.[20]

To investigate the effect of Rule 5150, we examine whether investment banks' selection of comparable companies differs in the post-rule period, which is 2008 or later, compared with the pre-rule period, which is prior to 2008. We present the results in Internet Appendix Table IA5. Some evidence exists that banks choose comparable companies with higher valuations in the period following the regulatory change. If the difference for either one of the valuation multiples is positive, the banks tend to choose comps with higher valuations in the post-rule period. Regarding other characteristics, banks tend to choose smaller firms and less profitable firms following the implementation of FINRA Rule 5150.

8.4. Peer firm selection in successful or unsuccessful buyouts

We examine whether the peer firm selection is different in successful or unsuccessful buyout deals. We initially follow Strömberg (2008) and define buyout transactions as successful if the PE firms exit through an IPO, a sale to a strategic buyer, or a secondary buyout. We define buyout deals as unsuccessful if they exit through bankruptcy. Because some of the non-bankruptcies are likely also ex post unsuccessful, we further refine our approach by tracking the buyout purchase price and market value at exit. For exit through strategic sale or secondary buyout, we compute the ratio of the sale value to purchase price. For exit through IPO, we compute the ratio of the first day market value to purchase price. One issue with this measure of buyout return is that it is not benchmarked to market conditions. Thus, in the spirit of Kaplan and Weisbach (1992), we adjust our return measure using the Standard & Poor's (S&P) 500 index return (excluding dividends) for the same period. We then define buyouts, in addition to bankruptcies, as unsuccessful if the buyout returns minus S&P 500 index returns are less than zero.[21]

We use several data sources and manual searches to identify the exit status for the buyout transactions.[22] We are able to find exit status for a total of 273 deals: 74 (27.1%) exits through an IPO, 103 (37.7%) exits through a sale to a strategic buyer, 60 (22.0%) exits through a secondary buyout, 35 deals (12.8%) that ended in bankruptcy, and one deal (0.4%) that exited through a sale to management. The remaining buyout targets either are still private or have incomplete exit information. Thus, despite our best efforts, this sample is somewhat limited and potentially subject to selection bias.

To compute the buyout return measure, which is used to code some non-bankruptcies as unsuccessful outcomes, we need to estimate the purchase value and the sale value for each transaction. The purchase value is straightforward to collect, as it is simply the buyout transaction value, excluding liabilities, from SDC. The sale value is more difficult to estimate. Some exits can be matched with the IPO

[20] FINRA Rule 5150 requires enhanced disclosures in the fairness opinions of conflicts of interests or prior business relations the banks could have. Banks also must disclose the compensation structure of the deal, which could impact banks' incentives. The rule also requires that the banks have an internal fairness opinion committee to evaluate the valuation process. See https://www.finra.org/rules-guidance/rulebooks/finra-rules/5150.

[21] Our measure of success has limitations and perhaps does not perfectly reflect the returns to buyouts. For example, we, unfortunately, do not observe the private firm investor cash inflows or outflows that occurred between the purchase and exit dates, which can impact the buyout returns.

[22] For the 606 deals that SDC identifies as leverage buyout transactions or transactions that involve a financial sponsor, we exclude 44 withdrawn deals, which leaves 562 completed deals. To measure buyout deal outcome, we first match deals with the SDC IPO and bankruptcy database and the SDC M&A data set, the latter of which allows us to identify exits via sale to a strategic buyer or another PE firm. Most of the buyout sample remains unmatched, which requires us to search for outcomes for each transaction.

or M&A transaction value, excluding liabilities, from SDC or market equity value from CRSP. For deals that cannot be matched, we search news articles to identify the exit market value. We are able to identify 70 buyout deals that can be classified as unsuccessful based on our buyout return measure, and we put these deals in the unsuccessful group, which already includes bankruptcies.

We use these data to investigate whether peer selections systematically differ by exit status. We report the results in Internet Appendix Table IA6. Banks are less likely to select peers with low EV/EBITDA in buyouts with unsuccessful exits compared with successful exits (the differences in coefficients on both the positive and negative EV/EBITDA difference among the unsuccessful buyouts and successful buyouts are statistically significant). These results provide some evidence that banks select peers with low valuations in transactions that are ex post more successful and select peers with high valuations in transactions that are ex post unsuccessful, suggesting that the management-affiliated buyer potentially overpaid. These findings, however, are inconclusive, as M/B gives insignificant results.

In addition to explicitly tracking the exit status, we separate buyout deals completed during 2006 to 2008 and classify these deals as unsuccessful (as a large fraction of that cohort of buyouts were completed at, or near, the peak of the market and resulted in unsuccessful exits for the PE firms). This classification has the advantage of not relying on the availability of the information on each transaction's exit status. We report the results in Internet Appendix Table IA6. Relative to buyout transactions completed in other years, banks again are more likely to select peers with high EV/EBITDA multiples in buyouts conducted between 2006 and 2008. The difference in coefficients on $|Diff\ (EV/EBITDA)|^{-}$ is statistically significant.

Overall, our investigation of banks' peer selection based on the successfulness of the buyout transactions provides suggestive evidence that banks choose peers with higher valuations, which could lead to overpayment, in unsuccessful buyout transactions. This evidence is not, however, particularly strong, as we find statistical significance only using one of the valuation measures in each analysis.

8.5. Overlapping peers in deals with multiple banks

We investigate how often investment banks select the same peer in deals in which the target firm hires more than one investment bank. To conduct this analysis, we identify 398 such deals, representing 10.2% of our full sample of deals. This percentage is similar to the 9.5% reported in Liu (2020) in her full sample period (1996 to 2013).

We compute the Jaccard similarity index to measure the extent to which investment banks choose overlapping comparable companies. The Jaccard similarity index is defined as the size of the intersection divided by the size of the union of the comparable company sets by each bank for the same target firm. By construction, the Jaccard similarity index is between 0% and 100%. The average (median) Jaccard similarity index for our 398 deals with multiple fairness opinions is 63.1% (63.4%). Using the median number of comparable firms chosen by each bank (eight) applied to our two-opinions sample, a 63.1% Jaccard similarity index means that among the eight peers selected by each bank, 6.2 of them are the same firm [6.2 / (16 - 6.2) = 0.633]. This high overlap in selection among banks suggests that the comparable firms are carefully chosen by the investment banks.

We further investigate whether systematic differences exist in the peer selection and relative valuation relation based on whether a peer is selected by more than one bank in deals with multiple fairness opinions. We report the results in Internet Appendix Table IA7. We do not find significant differences between peers that are in the intersection versus those that are not.

9. Concluding remarks

This paper provides novel evidence on how investment banks estimate firm value for target firms in M&A transactions. We focus on how banks choose peer firms in the comparable companies analysis, which is one of the leading valuation approaches in practice. The choice of peer firms is arguably the most important step in determining valuations for the comparable companies approach. Despite its popularity in practice, academic evidence on the selection of peer firms in M&As is limited.

Using unique data, we reveal several interesting patterns. Though SIC codes, particularly three- and four-digit ones, often suggest otherwise, banks tend to choose peer firms that operate in the same industry, particularly the same product market space, as the target. Further, banks tend to strategically select peer firms that are large, high growth firms with relatively high valuation multiples, all of which are positively related to deal premiums. We also perform analysis in the cross section of deals, which yields results that differ with target management and investment bank incentives. For example, in management buyout deals, which provide incentives for managers to negotiate a lower target price, we find some evidence, though not definitive, that banks choose peer firms with relatively low valuations. In addition, banks choose peers with higher valuations in deals that follow the implementation of FINRA Rule 5150. Top-tier banks focus on choosing large firms and firms with higher product similarity. Finally, some evidence, albeit weak, shows that banks choose peers with higher valuations in unsuccessful buyout transactions (potentially leading to overpayment in those deals).

On balance, our evidence is consistent with the notion that target firm advisors attempt to boost the target firm's value by selecting peers with high valuation multiples to negotiate a higher offer price. These findings contribute important evidence to the M&A literature and the literature on equity valuation.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2021.09.006.

Appendix A. Variable definitions

Variable	Definition
Industry characteristics	
Same Target SIC 1	Indicator variable equal to one if a potential peer is in the same one-digit Standard Industrial Classification (SIC) of the target firm. We obtain firm SIC codes from Compustat historical SIC code.
Same Target SIC 2	Indicator variable equal to one if a potential peer is in the same two-digit SIC of the target firm.
Same Target SIC 3	Indicator variable equal to one if a potential peer is in the same three-digit SIC of the target firm.
Same Target SIC 4	Indicator variable equal to one if a potential peer is in the same four-digit SIC of the target firm.
Same Target TNIC 2	Indicator variable equal to one if a potential peer is in the same two-digit Text-based Network Industry Classifications (TNIC; Hoberg and Phillips, 2010) of the target firm.
Same Target TNIC 3	Indicator variable equal to one if a potential peer is in the same three-digit TNIC (Hoberg and Phillips, 2010) of the target firm.
Same Bidder SIC 1	Indicator variable equal to one if a potential peer is in the same one-digit SIC of the bidder firm.
Same Bidder SIC 2	Indicator variable equal to one if a potential peer is in the same two-digit SIC of the bidder firm.
Same Bidder SIC 3	Indicator variable equal to one if a potential peer is in the same three-digit SIC of the bidder firm.
Same Bidder SIC 4	Indicator variable equal to one if a potential peer is in the same four-digit SIC of the bidder firm.
Same Bidder TNIC 2	Indicator variable equal to one if a potential peer is in the same two-digit TNIC (Hoberg and Phillips, 2010) of the target firm.
Same Bidder TNIC 3	Indicator variable equal to one if a potential peer is in the same three-digit TNIC (Hoberg and Phillips, 2010) of the target firm.
Product Similarity (Target)	Pairwise product similarity score between the potential peer and target firms according to Hoberg and Phillips (2010).
Product Similarity (Bidder)	Pairwise product similarity score between the potential peer and bidder firms according to Hoberg and Phillips (2010).
Target Uniqueness	One minus the average of the product similarity scores between the target firm and each of its ten closest rivals. The closest rivals are the ten firms having the highest product similarity scores with the target firm.
Bidder Uniqueness	One minus the average of the product similarity scores between the bidder firm and each of its ten closest rivals. The closest rivals are the ten firms having the highest product similarity scores with the target firm.
Firm characteristics and valuation multiples	
Market Cap (millions of dollars)	Market capitalization, in millions of dollars, measured by the number of shares outstanding multiplied by the stock price for the fiscal year prior to the merger announcement (Compustat item: PRCC_F*CSHO).
Sales Growth	Firm's sales growth ratio, measured as the yearly change in sales, scaled by the previous year's sales.
EBITDA Margin	Ratio of earnings before interest, taxes, depreciation, and amortization (Compustat item: EBITDA) to total sales (Compustat item: SALE).
Asset Turnover	Ratio of a firm's total sales (Compustat item: SALE) to total assets (Compustat item: AT).
M/B	Ratio of the market value of equity to the book value of equity. Following Davis, Fama, and French (2000), we measure annual book equity as stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (Compustat item: TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (SEQ) if it is available. If not, we measure stockholders' equity as the book value of common equity (Compustat item: CEQ) plus the par value of preferred stock (Compustat item: PSTK) or the book value of assets (Compustat item: AT) minus total liabilities (Compustat item: LT). Depending on availability, we use redemption (Compustat item: PSTKRV), liquidating (Compustat item: PSTKL), or par value (Compustat item: PSTK) for the book value of preferred stock.
EV/EBITDA	Ratio of enterprise value to earnings before interest, taxes, depreciation, and amortization (Compustat item: EBITDA). Following Loughran and Wellman (2011), we measure enterprise value (EV) as the market value of equity (Compustat item: PRCC_F*CSHO) plus the total debt [Compustat items: DLC and DLTT (short- and long-term debt)] plus preferred stock value (Compustat item: PSTKRV) minus cash and short-term investments (Compustat item: CHE). Only firms with positive EBITDA are included for the calculation of this variable.
Diff (Market Cap)	Potential peer firm's market capitalization (in natural logarithm) minus target firm's market capitalization (in natural logarithm). In this case, "difference relative to bidder" is defined as the potential peer firm's market capitalization (in natural logarithm) minus bidder firm's market capitalization (in natural logarithm).
Diff (Sales Growth)	Potential peer firm's sales growth minus target firm's sales growth. In this case, "difference relative to bidder" is defined as the potential peer firm's sales growth minus bidder firm's sales growth.
Diff (EBITDA Margin)	Potential peer firm's EBITDA margin minus target firm's EBITDA margin. In this case, "difference relative to bidder" is defined as the potential peer firm's EBITDA margin minus bidder firm's EBITDA margin.
Diff (Asset Turnover)	Potential peer firm's asset turnover ratio minus target firm's asset turnover ratio. In this case, "difference relative to bidder" is defined as the potential peer firm's asset turnover ratio minus bidder firm's asset turnover ratio.
Diff (M/B)	Potential peer firm's market-to-book (M/B) ratio minus target firm's M/B ratio. In this case, "difference relative to bidder" is defined as the potential peer firm's M/B ratio minus bidder firm's M/B ratio.

(*continued on next page*)

(*continued*)

Variable	Definition
Diff (EV/EBITDA)	Potential peer firm's EV/EBITDA ratio minus target firm's EV/EBITDA ratio. In this case, "difference relative to bidder" is defined as the potential peer firm's EV/EBITDA ratio minus bidder firm's EV/EBITDA ratio.
Deal and investment bank characteristics	
Deal Value (millions of dollars)	Transaction value as reported by the Securities Data Company (SDC).
Premium (-84)	Offer price obtained from SDC relative to target stock price 84 trading days prior to the merger announcement.
CAR (-84, 126)	Target cumulative abnormal returns (CARs) over the event window (-84, +126) using market adjusted returns from the Center for Research in Security Prices value-weighted index, where day 0 is the merger announcement date.
Product Similarity (Bidder & Target)	Pairwise product similarity score between bidder and target firm according to Hoberg and Phillips (2010). We set the missing values as zero in Table 9.
Public Acquirer	Indicator variable equal to one if bidder status reported by SDC is public.
Tender Offer	Indicator variable equal to one if SDC reports that the deal is a tender offer.
Buyout	Indicator variable equal to one if SDC reports that the deal is a buyout deal.
All Stock	Indicator variable equal to one if SDC reports that a deal uses all stock financing.
All Cash	Indicator variable equal to one if SDC reports that a deal uses all cash financing.
Multiple Bidder	Indicator variable equal to one if SDC reports more than one bidder in a deal.
Withdrawn	Indicator variable equal to one if a deal is withdrawn.
Hostile	Indicator variable equal to one if the deal attitude reported by SDC is hostile.
Toehold	Indicator variable equal to one if SDC reports that the bidder holds 5% or more of the target firm's shares.
Top 8 Advisor	Indicator variable equal to one if the target advisor is ranked as a top eight advisor in the deal announcement year. Each year, we rank investment banks based on the number of fairness opinions containing comparable companies analysis they issue over the preceding five-year window. We track mergers between investment banks during our sample period. If Bank A acquires Bank B in year *t*, we compute the number of fairness opinions containing comparable companies analysis issued by each bank separately before year *t* and compute combined number of fairness opinions containing comparable companies analysis after year *t* to rank advisors.
FINRA Rule 5150	Indicator variable equal to one if a deal is announced in 2008 or after.

Appendix B. An example of investment bank valuation during merger negotiations

Target: BEI Technologies, Inc.

Acquirer: Schneider Electric SA

Securities and Exchange Commission filing: Form SC 14D9[23]

The below content is extracted from the merger filing, Section "Background of the Offer"

In early 2005, Company management discussed with members of the Board the possibility of having UBS Securities LLC ("UBS") survey the market to determine whether there might be potential acquirers for the Company before the Company sought to undertake strategic initiatives, such as raising additional capital. As a result of those discussions between Company management and members of the Board, the Company directed representatives of UBS to arrange meetings with various potential acquirers.

On March 10, 2005, in connection with the Company's intent to identify and hold discussions with potential acquirers, the Company entered into an initial engagement letter for advisory services with UBS. Subsequently, the Company and UBS entered into an engagement letter dated as of May 1, 2005 pursuant to which UBS was engaged as the Company's exclusive financial adviser in connection with the possible acquisition of the Company.

From February 28, 2005 through March 17, 2005, representatives of UBS contacted six potential acquirers, including Parent.

From March 25, 2005 through May 2, 2005, representatives of UBS participated in several discussions with representatives of Parent and Merrill Lynch, Parent's financial adviser, about the potential acquisition of the Company by Parent.

On May 2, 2005, Mr. Pilaud sent a written non-binding proposal to UBS indicating that Parent would be interested in acquiring all of the outstanding capital stock of the Company for an enterprise value in the range of $480 million to $555 million, which Parent calculated to be a per Share price, payable in cash, between $30 and $35. Parent's non-binding proposal also requested that the Company agree to negotiate exclusively with Parent for a period of four weeks.

On June 20, 2005, the non-employee Board members participated in a telephone call with representatives of UBS and Cooley Godward to discuss the status of the discussions with Parent. Representatives of UBS also presented to the Board members participating in the call certain preliminary financial analyses. On June 21, 2005, UBS sent a letter to Mr. Pilaud requesting that Parent submit a non-binding letter of interest with a more specific price per Share to the Company by June 24, 2005. On June 23, 2005 Mr. Pilaud called Mr. Crocker and indicated that Parent needed more time to conduct due diligence and that it would not be able to indicate a specific price per Share by June 24,

[23] See https://www.sec.gov/Archives/edgar/data/1041866/000104746905020662/a2161594zsc14d9.htm.

2005. The next day, Mr. Pilaud called Mr. Crocker and indicated that Parent would be able to send a non-binding letter of interest to the Company indicating a specific price per Share by June 28, 2005.

On July 12, 2005, at a meeting of the Board, representatives of UBS gave a presentation detailing certain preliminary financial analyses and the Board discussed the transaction, the draft Merger Agreement and the progress of price negotiations. Representatives of Cooley Godward participated in this meeting and discussed with the Board various proposed terms of the draft Merger Agreement and related agreements.

On July 17, 2005, Mr. Crocker and Mr. Pilaud discussed by telephone the draft Merger Agreement and various other aspects of the proposed transaction. During this conversation Mr. Pilaud confirmed that Parent was prepared to pay $35 per Share in cash for the Company.

On July 21, 2005, at a telephonic meeting of the Board to review and consider Parent's proposal, representatives of Cooley Godward updated the Board on the status of the negotiations and summarized the terms of the form of Merger Agreement and ancillary agreements that had been circulated to the Board in advance of the meeting. UBS presented to the Board the financial analyses of UBS in connection with UBS' consideration of the fairness, from a financial point of view, of the $35 in cash per share (the "Consideration") to be received by the holders of shares of Common Stock in the tender offer made pursuant to the Merger Agreement and in the Merger (the "Transaction") (other than Mr. Crocker and the beneficiaries of any trusts holding shares of Common Stock and for which he acts as trustee and any of his affiliates (collectively, the "Crocker Parties")). UBS also delivered its opinion to the Board, dated July 21, 2005, that as of such date and based upon and subject to the various assumptions made, procedures followed, matters considered and qualifications and limitations described in the opinion, the Consideration to be received by the holders of shares of the Common Stock in the Transaction (other than the Crocker Parties) was fair, from a financial point of view, to such holders. There was an extended discussion among the participants in the meeting.

Later in the day, the Company, Parent and the Purchaser executed the Merger Agreement and the transaction was publicly announced the following day before the opening of the Paris Bourse.

On August 3, the target firm filed Form SC14D9 with the SEC.

On October 6, the deal is completed.

Appendix C. An example of comparable company analysis

Target: BEI Technologies, Inc.

Acquirer: Schneider Electric SA

The below content is extracted from the merger filing, Section "Opinion of the Company's Financial Advisor"

Opinion of UBS

The Company's board of directors selected UBS as its financial adviser in connection with the transaction contemplated by the Merger Agreement because UBS is an internationally recognized investment banking firm with substantial experience in similar transactions. UBS rendered its opinion to the Company's board of directors that, as of July 21, 2005 and based upon and subject to the various assumptions made, procedures followed, matters considered and limitations described in the opinion, the $35.00 per share in cash (the "Consideration") to be received by the holders of shares of Common Stock in the tender offer made pursuant to the Merger Agreement and in the Merger (together, the "Transaction") (other than Mr. Charles Crocker and the beneficiaries of any trusts holding shares of Common Stock and for which he acts as trustee and any of his affiliates (collectively, the "Crocker Parties")) was fair, from a financial point of view, to such holders.

Selected Companies Analysis

UBS reviewed and compared certain financial information for the Company to corresponding financial information, ratios and public market multiples for the following selected publicly traded industrial technology companies:

Automotive Concentration

- Gentex Corporation
- Melexis Microelectronic Systems
- Stoneridge, Inc.
- TT Electronics plc

Industrial Technology Concentration

- Amphenol Corporation
- CTS Corporation
- Molex, Inc.
- Rofin-Sinar Technologies, Inc.

Aerospace and Defense Concentration

- EDO Corporation
- Esterline Technologies

Although the selected companies were used for comparison purposes, the businesses of no selected company were either identical or directly comparable to the businesses of the Company. Accordingly, UBS' comparison of the selected companies to the Company and analysis of the results of such comparisons was not purely mathematical, but instead necessarily involved complex considerations and judgments concerning differences in financial and operating characteristics and other factors that could affect the relative values of the selected companies and of the Company.

References

Albuquerque, A., De Franco, G., Verdi, R., 2013. Peer choice in CEO compensation. J. Financ. Econ. 108, 160–181.

Alford, A., 1992. The effect of the set of comparable firms on the accuracy of the price-earnings valuation method. J. Account. Res. 30, 94–108.

Andrade, G., Mitchell, M., Stafford, E., 2001. New evidence and perspectives on mergers. J. Econ. Perspect. 15, 103–120.

Angrist, J., 2001. Estimation of limited dependent variable models with dummy endogenous regressors: simple strategies for empirical practice. J. Bus. Econ. Stat. 19, 2–28.

Bao, J., Edmans, A., 2011. Do investment banks matter for M&A returns? Rev. Financ. Stud. 24, 2286–2315.

Bargeron, L.L., Schlingemann, F.P., Stulz, R.M., Zutter, C.J., 2008. Why do private acquirers pay so little compared to public acquirers? J. Financ.Econ. 89, 375–390.

Bates, T., Becher, D., 2017. Bid resistance by takeover targets: managerial bargaining or fad faith? J.f Financ.Quantitat. Anal. 52, 837–866.

Beatty, R., Riffe, S., Thompson, R., 1999. The method of comparables and tax court valuations of private firms: an empirical investigation. Account. Horiz. 13, 177–199.

Bebchuk, L., Kahan, M., 1989. Fairness opinions: how fair are they and what can be done about it. Duke L. J. 38, 27–53.

Betton, S., Eckbo, B.E., Thorburn, K., 2008. Corporate takeovers. In: Eckbo, B. E.. Handbook of Empirical Corporate Finance 2, 291–429.

Bizjak, J., Lemmon, M., Naveen, L., 2008. Does the use of peer groups contribute to higher pay and less efficient compensation? J. Financ. Econ. 90, 152–168.
Bizjak, J., Lemmon, M., Nguyen, T., 2011. Are all CEOs above average? An empirical analysis of compensation peer groups and pay design. J. Financ. Econ. 100, 538–555.
Bhojraj, S., Lee, C., 2002. Who is my peer? A valuation-based approach to the selection of comparable firms. J. Account. Res. 40, 407–439.
Bowers, H., Miller, R., 1990. Choice of investment banker and shareholders' wealth of firms involved in acquisitions. Financial Manag. 19, 34–44.
Cadman, B., Carter, M., 2014. Compensation peer groups and their relation with CEO pay. J. Manage. Account. Res. 26, 57–82.
Cain, M., Denis, D., 2013. Information production by investment banks: evidence from fairness opinions. J. Law Econ. 56, 245–280.
Calomiris, C., Hitscherich, D., 2007. Banker fees and acquisition premia for targets in cash tender offers: challenges to the popular wisdom on banker conflicts. J. Empir. Leg. Stud. 4, 909–938.
Chemmanur, T., Fulghieri, P., 1994. Investment bank reputation, information production, and financial intermediation. J. Finance 49, 57–79.
Davidoff, S., 2006. Fairness opinions. Am. Univ. Law Rev. 55, 1557–1625.
Davidoff, S., Makhija, A., Narayanan, R., 2011. Fairness opinions in mergers and acquisitions. In: The Art of Capital Restructuring: Creating Shareholder Value through Mergers and Acquisitions. John Wiley & Sons, Hoboken, NJ, pp. 483–494.
Davis, J., Fama, E., French, K., 2000. Characteristics, covariances, and average returns: 1929 to 1997. J. Finance 55, 389–406.
DeAngelo, L., 1986. Accounting numbers as market valuation substitutes: a study of management buyouts of public stockholders. Account. Rev. 61, 400–420.
DeAngelo, L., 1990. Equity valuation and corporate control. Account. Rev. 65, 93–112.
De Vaan, M., Elbers, B., DiPrete, T., 2019. Obscured transparency? Compensation benchmarking and the biasing of executive pay. Manage. Sci. 65, 4299–4317.
Eaton, G., Liu, T., Officer, M., 2021. Rethinking measures of mergers and acquisitions deal premiums. J. Financ. Quantit. Anal. 56, 1097–1126.
Elson, C., 1992. Fairness opinions: are they fair or should we care? Ohio State Law J. 53, 951–1003.
Fama, E., French, K., 1992. The cross section of expected stock returns. J. Finance 47, 427–465.
Fang, L., 2005. Investment bank reputation and the price and quality of underwriting services. J. Finance 60, 2729–2761.
Faulkender, M., Yang, J., 2010. Inside the black box: the role and composition of compensation peer groups. J. Financ. Econ. 96, 257–270.
Golubov, A., Petmezas, D., Travlos, N., 2012. When it pays to pay your investment banker: new evidence on the role of financial advisors in M&As. J. Finance 67, 271–311.
Gompers, P., Kaplan, S., Mukharlyamov, V., 2016. What do private equity firms say they do? J. Financ. Econ. 121, 449–476.
Guenther, D., Rosman, A., 1994. Differences between compustat and CRSP SIC codes and related effects on research. J. Account. Econ. 18, 115–128.
Hafzalla, N., 2009. Managerial incentives for discretionary disclosure: evidence from management leveraged buyouts. Rev. Account. Stud. 14, 507–533.
Haire, M., 2000. The fiduciary responsibilities of investment bankers in change-of-control transactions: in re Daisy Systems Corp. c 55, 883–916.
Harford, J., 2005. What drives merger waves? J. Financ. Econ. 77, 529–560.
Hoberg, G., Phillips, G., 2010. Product market synergies and competition in mergers and acquisitions: a text-based analysis. Rev. Finan. Studies 23, 3773–3811.
Hoberg, G., Phillips, G., 2016. Text-based network industries and endogenous product differentiation. J. Polit. Econ. 124, 1423–1465.
Holthausen, R., Zmijewski, M., 2012. Valuation with market multiples: how to avoid pitfalls when identifying and using comparable companies. J. Appl. Corp. Finance 24, 26–38.
Huang, Y., Walkling, R., 1987. Target abnormal returns associated with acquisition announcements: payment, acquisition form, and managerial resistance. J. Finan. Econ. 19, 329–349.
Kahle, K., Walkling, R., 1996. The impact of industry classifications on financial research. J. Finan. Quant. Anal. 31, 309–335.
Kaplan, S., Ruback, R., 1995. The valuation of cash flow forecasts: an empirical analysis. J. Finance 50, 1059–1093.
Kaplan, S., Stromberg, P., 2009. Leveraged buyouts and private equity. J. Econ. Perspect. 23, 121–146.
Kaplan, S., Weisbach, M., 1992. The success of acquisitions: evidence from divestitures. J. Finance 47, 107–138.
Kim, M., Ritter, J., 1999. Valuing IPOs. J. Financ. Econ. 53, 409–437.
Kisgen, D., Qian, J., Song, W., 2009. Are fairness opinions fair? The case of mergers and acquisitions. J. Financ. Econ. 91, 179–207.
Koller, T., Goedhart, M., Wessels, D., 2005. Valuation: Measuring and Managing the Value of Companies, Fourth Edition. John Wiley & Sons, Hoboken, NJ.
Lancaster, T., 2000. The incidental parameter problem since 1948. J. Econometrics 95, 391–413.
Li, K., Liu, T., Wu, J., 2018. Vote avoidance and shareholder voting in mergers and acquisitions. Rev. Financ. Studies 31, 3176–3211.
Liu, T., 2020. The information provision in the corporate acquisition process: why target firms obtain multiple fairness opinions. Account. Rev. 95, 287–310.
Loughran, T., Wellman, J., 2011. New evidence on the relation between the enterprise multiple and average stock returns. J. Financ. Quant. Anal. 46, 1629–1650.
Michael, D., 1992. Untenable status of corporate governance listing standards under the Securities Exchange Act. Business Lawyer 4, 1461–1504.
Michel, A., Shaked, I., Lee, Y., 1991. An evaluation of investment banker acquisition advice: the shareholders' perspective. Financ. Manag. 20, 40–49.
Moeller, S., Schlingemann, F., Stulz, R., 2004. Firm size and the gains from acquisitions. J. Financ. Econ. 73, 201–228.
Offenberg, D., Pirinsky, C., 2015. How do acquirers choose between mergers and tender offers? J. Financ. Econ. 116, 331–348.
Officer, M., 2003. Termination fees in mergers and acquisitions. J. Financ. Econ. 69, 431–467.
Officer, M., 2007. The price of corporate liquidity: acquisition discounts for unlisted targets. J. Financ. Econ. 83, 571–598.
Officer, M., Ozbas, O., Sensoy, B., 2010. Club deals in leveraged buyouts. J. Financ. Econ. 98, 214–240.
Perry, S., Williams, T., 1994. Earnings management preceding management buyout offers. J. Account. Econ. 18, 157–179.
Pichler, P., Wilhelm, W., 2001. A theory of the syndicate: form follows function. J. Finance 56, 2237–2264.
Rau, P., 2000. Investment bank market share, contingent fee payments, and the performance of acquiring firms. J. Financ. Econ. 56, 293–324.
Schwert, G., 1996. Markup pricing in mergers and acquisitions. J. Financ. Econ. 41, 153–192.
Schwert, G., 2000. Hostility in takeovers: in the eyes of the beholder? J. Finance 55, 2599–2640.
Servaes, H., Zenner, M., 1996. The role of investment banks in acquisitions. Rev. Financ. Studies 9, 787–815.
Strömberg, P., 2008. The new demography of private equity. In: Globalization of Alternative Investment: Working Papers Volume 1: The Global Economic Impact of Private Equity Report 2008. World Economic Forum, Geneva, Switzerland, pp. 3–26.