Bidder-Specific Synergies and the Evolution of Acquirer Returns

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Olivier Dessaint
INSEAD

B. Espen Eckbo
Dartmouth College and ECGI

Andrey Golubov
University of Toronto

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Abstract

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Keywords: Mergers and acquisitions, acquirer returns, bidder-specific synergies, bidder uniqueness

JEL Classifications: G14, G34

Olivier Dessaint
Assistant Professor of Finance
INSEAD, Finance Department
Boulevard de Constance
77305 Fontainebleau, France
e-mail: olivier.dessaint@insead.edu

B. Espen Eckbo
Tuck Centennial Professor of Finance
Dartmouth College, Tuck School of Business at Dartmouth
100 Tuck Hall
Hanover, NH 03755, United States
phone: +1 603 646 3953
e-mail: b.espen.eckbo@dartmouth.edu

Andrey Golubov*
Assistant Professor of Finance
University of Toronto, Rotman School of Management
105 St. George Street
Toronto, ON M5S 3E6, Canada
phone: +1 416 946 8427
e-mail: Andrey.Golubov@rotman.utoronto.ca

*Corresponding Author

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Olivier Dessaint† B. Espen Eckbo‡ Andrey Golubov§

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Abstract

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†INSEAD, olivier.dessaint@insead.edu

‡Tuck School of Business at Dartmouth College, b.espen.eckbo@dartmouth.edu

§Rotman School of Management, University of Toronto, andrey.golubov@rotman.utoronto.ca

1 Introduction

In their reviews of first-generation empirical estimates of takeover gains, Jensen and Ruback (1983) and Roll (1986) made two important observations. First, acquirer announcement returns are positive but small on average. Second, target shareholders appear to capture the lion's share of synergy gains. More than three decades later, an expansive literature — benefiting from access to large-scale electronic databases — largely confirms these two conclusions (see, e.g., Betton, Eckbo, and Thorburn (2008)). This literature also proposes several potential explanations for why average bidder returns are low. The hypotheses range from competition among bidder firms to more complex explanations involving bidder agency costs, managerial hubris, or measurement issues due to market deal anticipation and revelations about bidder stand-alone values. However, no single view has emerged as the dominant explanation for continued lackluster bidder performance.

We offer a new perspective on this literature by studying the evolution of announcement returns over time in a comprehensive sample of U.S. acquirers. Our focus on the time-series evolution is motivated by the profound changes in the capital markets and the market for corporate control over the last four decades. Empirical evidence suggests that corporate governance practices in listed firms have improved (Gillan and Starks, 2007), that executives and directors are now more highly educated (Krueger, Landier, and Thesmar, 2015), and that financial markets may have become more open and informative (Bai, Phillipon, and Savov, 2016). It is reasonable to expect that such broad-based developments have also resulted in improved corporate decision-making, including acquisition decisions as one of the most prominent and consequential forms of corporate investment. And yet, there is little evidence of any such improvement. It is as if none of these developments have benefited acquirers and their shareholders.

In this paper we show that existing evidence on the evolution of average acquirer returns is incomplete, as it masks two fundamental but opposing underlying trends in the data. Our starting point is the observation that the composition of listed firms — the focus of all studies of acquirer returns — has changed dramatically over the last decades (Fama and French, 2004; Doidge, Karolyi, and Stulz, 2017; Eckbo and Lithell, 2020). Such changes may have profound implications for the evolution of acquirer returns, because much of the variation in bidder takeover gains is firm-specific (Golubov, Yawson, and Zhang, 2015). Indeed, our first contribution is to demonstrate that a change in the composition of bidders has confounded a general trend towards *higher* acquirer returns. Holding bidder composition constant, acquirer returns have been on the rise over much of the past four decades — a finding we refer to as a common trend. This increase has gone undetected because the mix of bidders undertaking acquisitions has changed in a way that offsets the upward common trend. We refer to this offsetting force as a composition effect. Having established the two opposing trends in the data, our second contribution is to examine their economic nature, culminating in a novel theory of what we call bidder-specific synergies.

We begin by documenting new stylized facts about bidder takeover gains. In line with prior research on the evolution of acquirer returns (e.g., Moeller, Schlingemann, and Stulz (2005)), we show that average acquirer gains have remained close to zero and largely flat over the last four decades. This is true both unconditionally as well as after controlling for various firm- and deal-specific characteristics. In sharp contrast to this received wisdom, we uncover a strong positive time trend in acquirer returns when we further control for bidder composition via firm fixed effects. Holding bidder composition constant, acquirer returns have increased by as much as five percentage points relative to the 1980s. This common trend is broad-based: it is equally-present in acquisitions of public and private targets, in cash and stock deals, in focused and diversifying transactions, and in domestic and cross-border acquisitions.[1] Counteracting this common trend, the composition of bidders making acquisitions has changed significantly over time. We find that the average *bidder-specific* (i.e. fixed effect) component of acquirer returns has declined just enough to offset the rising common trend. Simulation analysis confirms the tight link between the two opposing trends.

In the second part of the paper we turn to theory to guide our interpretation of the new stylized facts. At a high level, our evidence indicates that the mix of bidders making acquisitions has changed. The nature of this change in bidder composition is therefore key to making sense of the temporal patterns we document. Golubov, Yawson, and Zhang (2015) argue that firm-specific heterogeneity in acquirer returns is likely due to "bidder-specific synergies, such as those arising from unique assets or skills". Building on their insight, we develop a simple theoretical framework that links announcement returns to merger-induced synergies and how unique they are to the winning bidder. Bidder uniqueness in our theory represents the degree of substitutability between potential rival bidders. For example, synergies are more bidder-specific when the bidder contributes a unique distribution network for the target's product and less bidder-specific when the target sells itself to a cash-rich buyer in order to fund its continued

[1]Moreover, the increase is present in both value-creative and value-destroying deals and robust to event windows of substantially varying length, ruling out explanations such as the efficiency and speed of market pricing.

operations. Since cash is fungible, synergies in the latter case are not unique to any particular bidder, and competition among perfect-substitute bidders drives down the share of synergies the ultimate buyer can extract. The main insight is that acquirer returns increase with the uniqueness of the winning bidder in terms of the resources it brings to the deal. This insight is new to the literature: while prior studies have focused on the role of similarity between the bidder and the target in determining synergies (e.g., Hoberg and Phillips (2010)), our theory highlights the role of similarity between potential rival bidders in determining bargaining power. We develop four empirical proxies for bidder uniqueness that closely follow the associated notion in our theoretical framework, namely, the (dis)similarity between the winning bidder and the latent second-best alternative buyer. Bidder uniqueness has a first-order effect on acquirer returns in the data: more unique bidders earn higher acquisition returns.

We then use our theoretical framework to help interpret the time-series evidence. Starting with the composition effect, we test whether the bidder-specific (fixed effect) component of acquirer returns reflects bidder uniqueness. We find that all four proxies for bidder uniqueness directly explain the variation in the estimated bidder fixed effects. Moreover, proxies for bidder uniqueness no longer explain acquirer returns when bidder composition is controlled for. Finally, we find that our bidder uniqueness proxies trend downward over time — just as the bidder-specific component of acquirer returns. The evidence is thus consistent with the composition effect reflecting a decline in bidder uniqueness. This implies that merger synergies, whatever their source, have become less unique to the winning bidder. Put differently, acquirers have become less differentiated from their latent competition in the takeover market.

This interpretation of the composition effect, in turn, generates testable predictions about the economic nature of the rising common trend in acquirer returns. In our theoretical framework, acquirer returns are positively related to bidder uniqueness and overall deal synergies. If bidder uniqueness has declined while average acquirer returns have not, then merger synergies *must* have contemporaneously increased. Using the public-target subsample as a laboratory, we find that combined firm abnormal returns and operating performance improvements — proxies for merger synergies — have indeed increased over time. Moreover, target firm returns have also increased, in line with declining bidder uniqueness benefiting targets through an improvement in their outside option. Overall, the evidence is consistent with a general increase in merger synergies that have become less bidder-specific over time.

We conclude the paper with exploratory evidence on the potential reasons for declining bidder uniqueness and rising merger synergies, linking our findings to the M&A and the broader finance literature.

Declining bidder uniqueness implies that the resources bidders bring to the negotiating table are becoming less scarce. We show that financing power — one known source of synergy gains — is no longer unique to the population of bidders, as other firms in the economy have seen a relaxation of their financing constraints. We also find that bidders are falling behind in terms of hard-to-replicate resources, such as knowledge capital arising from investment in innovation. As for the source of rising synergies, the analysis is notable for what does *not* work. First, learning through acquisition activity—discussed extensively in the literature—does not explain the upward trend we document. Second, we fail to find support for the hypothesis that temporal improvements in the quality of corporate governance resulted in improved deal-making over time. Third, we examine whether the increase in merger gains is related to the trend towards increased industry concentration in the U.S., but find no such statistical link. Finally, we do find some (weak) evidence on the link between the upward common trend in acquirer returns and changes in the composition of M&A advisors — as if acquirers have gravitated toward higher value-added advisors over time. However, the upward trend is also present in deals that likely involved no advisors. Overall, the origins of rising merger synergies is a puzzle to be resolved.

The rest of the paper is organized as follows. Section 2 describes our sample, while Section 3 establishes our basic results concerning the evolution of acquirer returns over time. Section 4 demonstrates how the time-series evidence can be rationalized within a simple theoretical framework of merger synergies and their specificity. Section 5 explores potential drivers of declining bidder uniqueness and rising merger synergies. We conclude in Section 6. The Internet Appendix contains various supplementary material referenced throughout the paper.

2 Sample selection and description

The M&A data come from Thomson Reuters SDC M&A database and cover all acquisitions (repurchases and recapitalizations excluded) announced by U.S. public firm during the period from January 1, 1981 to December 31, 2017 (37 years). Our sample selection steps, which yield a total of 23,553 deals by 5,356 distinct bidders, are as follows:

(1) Completed or withdrawn M&A deal announcements from Thomson Reuters SDC, excluding repurchases.

(2) Bidders are U.S. public firms listed on NYSE, AMEX, or Nasdaq with a market capitalization of at least \$1 million, excluding penny stocks (stock price below \$1).

(3) Targets are U.S. or foreign, public, private, or subsidiary firms.

(4) Deals are worth at least \$1 million and represent at least 1% of bidder market capitalization four days prior to the deal announcement.

(5) The bidder owns less than 50% of the target before the acquisition and is seeking a transfer of control.

(6) Deal announcements falling within 5 days of a quarterly earnings release are excluded.

(7) The bidder has sufficient data on CRSP and Compustat to compute announcement period returns and standard control variables.

(8) The acquirer conducts at least two deals over the sample period (same-day announcements are excluded).

Restriction (8) above ensures that we are able to control for bidder heterogeneity via bidder fixed effects. Note that this requirement is not onerous as it results in only a modest reduction in sample size: from 27,638 to 23,553 deals. That is, more than 85% of the deals in a typical M&A sample are undertaken by repeat acquirers.

Table 1 illuminates the panel structure of our data in terms of the number of deals per bidder and the time between deals. As shown in Panel A, as many as 1,706 bidders out of the total of 5,356 (32%) conduct at least 5 acquisitions over the sample period, representing 59% of the deal-level observations (13,814 out of 23,553). The most acquisitive bidder conducts 37 deals in our sample. Note that this understates the true acquisitiveness, as we have excluded deals whose announcements overlap with quarterly earnings releases (for event study purposes). Panel B shows the frequency distribution of the average number of months between successive deals by a given bidder, and the time between the first and last bids. A median bidder conducts an acquisition every 17 months, and the 75th percentile of the average time between bids is 40 months. Also important, bidders tend to be active for a relatively short-lived period: the median time between first and last bid is just over four years (53 months). The 75th percentile of the time between first and last bids is 128 months. In other words, 75% of bidders are active within a period of only 10 years. This evidence is important for the analysis below as it suggests that the composition of bidders changes substantially over the four decades spanning our sample period.

We use standard event study methodology to compute announcement returns for our sample bidders. For firms with multiple classes of common stock we compute the cumulative abnormal return (CAR) as the weighted-average of CARs for the different share classes with the respective market capitalizations as weights. For most of the analysis we base our conclusion on CARs for the seven-day event window $[-3, +3]$ centered on the announcement date (day 0). However, we show below that the main results are robust to alternative event windows, including $[-1, +1]$ and $[-2, +2]$, $[-5, +5]$. The benchmark return is the return predicted by the one-factor market model estimated over the period from 300 to 46 days prior to the first public bid announcement, using the CRSP value-weighted index as the market portfolio. In unreported results, we also find that the main results are robust to alternative factor models for generating expected returns. All return variables and financial ratios are winsorized at the 1st and 99th percentiles (we perform the winsorization by year in order to preserve trends, if any).[2]

Internet Appendix Tables 1 and 2 provide the definitions and descriptive statistics of all variables used in the analysis. Consistent with the extant literature (Betton, Eckbo, and Thorburn, 2008), the unconditional average acquirer CAR $[-3, +3]$ is positive but modest, with a mean (median) of 0.97% (0.33%). About 23% of the targets are public firms, with the remainder of the transactions targeting private or subsidiary companies. The majority of targets are domestic, with 13% of the targets being foreign (cross-border deals). Mean (median) relative size of the deal as percentage of acquirer market capitalization is 24% (9%). For the subset of public targets, we also estimate target CAR $[-3, +3]$ which averages about 22% (median of 19%). The mean (median) takeover premium relative to the stock price four weeks prior to the announcement is 46.29% (39.15%) We also compute the combined firm CAR $[-3, +3]$ as the weighted-average of acquirer and target CARs with the respective market capitalizations on day -4 as weights. Combined firm CAR, which may be interpreted as the overall synergy gain from the combination, has a mean (median) value of 1.79% (1.06%) in our sample.

Table 2 shows the annual distribution of mean and median acquirer CAR $[-3, +3]$, number of deals, mean and median deal value, and total deal value by year. In our analysis below, we benchmark the

[2] When working with the significantly smaller public-target subsample and the associated variables, we increase the by-year winsorized fraction to 2% at both ends. For event study purposes on the target side, we disregard follow-up bids for the same target, unless a year has passed since the resolution date of the previous bid, penny-stock targets (priced below $1), and announcements that fall within 5 days of the target's quarterly earnings announcement.

estimation of any temporal changes against M&A activity in the first decade of our sample, 1981-1989. Of the overall total of \$14+ trillion worth of M&A activity by U.S. firms, \$13.09 trillion occurs during 1990-2017. Moreover, as shown, annual average and median bidder CARs are small and mostly positive. Unconditionally, the evolution of acquirer returns over the four-decade sample period shows no particular patterns.

3 The evolution of acquirer returns

We develop and report our analysis of the evolution of acquirer returns in two steps. First, we estimate whether the average acquirer return has changed over time without controlling for bidder composition. This involves running a cross-sectional regression of acquirer CARs on year dummies, with controls for firm and deal characteristics as well as industry heterogeneity added progressively. In the second step, we replace industry fixed effects with bidder firm fixed effects. This allows us to estimate any temporal change in acquirer returns *unconfounded* by changes in bidder composition.

3.1 Regression specification with year dummies

In the first-step estimation we run the following three cross-sectional regressions, which successively add explanatory variables:

$$CAR[-3,+3]_i = \alpha + \mathbf{S}\mathbf{Y}_\mathbf{i}' + \epsilon_i \tag{1}$$

$$CAR[-3,+3]_i = \alpha + \mathbf{S}\mathbf{Y}_\mathbf{i}' + \mathbf{\Gamma}\mathbf{X}_\mathbf{i}' + \epsilon_i \tag{2}$$

$$CAR[-3,+3]_i = \alpha + \mathbf{S}\mathbf{Y}_\mathbf{i}' + \mathbf{\Gamma}\mathbf{X}_\mathbf{i}' + IndFE + \epsilon_i. \tag{3}$$

The vector $\mathbf{Y}$ includes 28 annual dummy variables for the deal announcement years 1990-2017, with all of the 1980s as the omitted category, and coefficients $\mathbf{S}$ estimate the change in average acquirer CAR $[-3, +3]$ relative to acquisitions announced during the 1981-1989 period. In other words, the estimated coefficients $\mathbf{S}$ are changes in the average acquirer CAR in the corresponding year relative to the average acquirer CAR observed during the 1980s.[3] $\mathbf{X}$ is a vector of observable firm and deal characteristics.

[3] Our inferences are unchanged when using only the first five years of the 1980s as the baseline period, as well as when we exclude the 1980s altogether and use the first five years of the 1990s as our benchmark.

In the second step, we replace industry fixed effects ($IndFE$) with bidder fixed effects ($BidderFE$):

$$CAR[-3,+3]_i \quad = \quad \alpha + \mathbf{S}\mathbf{Y}_{\mathbf{i}}' + \mathbf{\Gamma}\mathbf{X}_{\mathbf{i}}' + BidderFE + \epsilon_i. \tag{4}$$

We employ an extensive list of time-varying control variables $\mathbf{X}$, all of which have been shown to help explain the cross-sectional variation in bidder CARs by prior studies. Among bidder characteristics, we include (the log of) acquirer size, Tobins Q, stock price run-up, idiosyncratic stock return volatility, cash holdings, and leverage. The acquirer size control is particularly relevant given our focus on the evolution of gains, as firms tend to grow over time, and acquirer size has a robust negative effect on acquirer returns (Eckbo and Thorburn, 2000; Moeller, Schlingemann, and Stulz, 2004; Schneider and Spalt, 2019)). In terms of deal-specific variables, $\mathbf{X}$ includes industry relatedness of the deal, tender offer, hostility, and cross-border indicators, as well as a set of interactions of target type (public/private/subsidiary) and the method of payment (cash/stock).[4]

3.2 Baseline coefficient estimates

Table 3 and Figure 1 report our baseline coefficient estimate $\mathbf{S}$ and $\mathbf{\Gamma}$. The standard errors in parentheses are double-clustered by acquirer industry (2-digit SIC level) and by year. The column numbers in Table 3 correspond to the equation numbers above. To facilitate presentation, the table reports the estimates of $\mathbf{\Gamma}$ only and omits the year-dummy coefficient estimates $\mathbf{S}$. Instead, the latter are plotted in the four graphs in Figure 1 along with the associated 99% confidence intervals. The top two graphs plot the year-dummy coefficient estimates $\mathbf{S}$ for regression models (1) and (2), while the bottom two graphs report the estimates of $\mathbf{S}$ in regressions (3) and (4), respectively.

In the top left graph in Figure 1, which excludes all control variables, several of the year-dummy coefficient estimates are positive and statistically significant at the 1% level. However, their magnitudes are small and there is no monotonic temporal trend.[5] Adding the control variables $\mathbf{X}$ in Column (2) of Table 3 produces the year-dummy coefficient estimates in the top-right graph in Figure 1, which also does not show a noticeable time trend in average acquirer CARs. The coefficient estimates on the control

[4] *Subsidiary target x stock* is the omitted category and serves as the benchmark for interpreting the coefficients on the interaction terms.

[5] The large drop in average acquirer returns in year 2000 is consistent with the evidence of large negative bidder dollar returns following the collapse of the 'tech bubble' documented by Moeller, Schlingemann, and Stulz (2005). They attribute the large losses in that period to revelations about bidder stand-alone values.

variables in **X** are, however, consistent with prior literature. For example, the effect of acquirer size and stock price run-up on acquirer CAR is negative, while the effect of leverage is positive.[6] Moreover, as documented by earlier studies, acquisitions of public targets are associated with lower acquirer returns, in particular when the payment method is all-stock.[7]

Next, we add acquirer 2-digit SIC industry fixed effects—as commonly done in the extant literature—in Column (3) of Table 3. As shown in the lower left graph in Figure 1, this control for sectoral composition changes in the M&A market also does not produce a noticeable time trend in average acquirer CARs. Our findings thus far are consistent with the extant literature that shows no improvement in average acquirer returns over time (Rosen, 2006; Netter, Stegemoller, and Wintoki, 2011). While Alexandridis, Antypas, and Travlos (2017) document an up-tick in average acquirer gains in the years following the financial crisis of 2007-2008, which is detectable in our Figure 1, the figure also shows through our longer sample period that this up-tick has largely reversed by the end of 2017.

3.3 Controlling for bidder composition effects

We now turn to the striking positive time trend seen in the lower-right graph in Figure 1. As shown in Column (4) of Table 3, this time trend in average bidder CARs emerges after we replace industry fixed effects with bidder fixed effects. This replacement helps control for the possibility that acquirers conducting acquisitions late in the sample period are fundamentally different—in terms of unobservable heterogeneity—from those conducting acquisitions early on. Our inclusion of firm fixed effects is also motivated by evidence in Golubov, Yawson, and Zhang (2015), who find that time-invariant latent firm-specific attributes are a major determinant of acquirer CARs.

In the estimates in the bottom right chart in Figure 1, the estimated coefficients on the year indicators show a surprisingly smooth monotonic upward trend. In the last year of our sample (2017), the average acquirer CAR is 5.4 percentage points higher than the average acquirer CAR during the benchmark period (the 1980s). This conditional increase is economically large considering that the unconditional acquirer CAR in our sample averages 0.97% (median 0.33%) over the sample period (Table 2).[8]

[6] E.g., Moeller, Schlingemann, and Stulz (2004), Rosen (2006), Maloney, McCormick, and Mitchell (1993), and Betton, Eckbo, Thompson, and Thorburn (2014).

[7] E.g., Travlos (1987), Fuller, Netter, and Stegemoller (2002), Faccio, McConnell, and Stolin (2006), and Eckbo, Makaew, and Thorburn (2018).

[8] Notice also that the addition of firm fixed effects mitigates the sharp decline in average acquirer returns in year 2000 documented by Moeller, Schlingemann, and Stulz (2005).

The fact that acquirer returns are largely flat when we do not control for bidder composition—and trending upward when we do—suggests that there has been a change in the average bidder-specific component of acquirer returns. In other words, there must have been an influx of "low fixed effect bidders" over the sample period. To examine this proposition, we record the estimated bidder fixed effects from the regression specification in Column (4) of Table 3 and regress them on year dummies, once again omitting dummies for all of the 1980s to serve as a benchmark:

$$\widehat{BidderFE}_i \quad = \quad \alpha + \mathbf{\Theta Y_i'} + \epsilon_i. \tag{5}$$

The resulting coefficients $\mathbf{\Theta}$ show the change in the average bidder fixed effect for all bidders conducting deals in a given year relative to the average bidder fixed effect in the benchmark period.[9] We run two additional specifications where we progressively add controls for i) time-varying deal and bidder characteristics, and ii) industry dummies (at the 2-digit SIC level). These three regressions are similar to those in columns (1), (2), and (3) of Table 3, except that the dependent variable is the estimated bidder fixed effect.

The upper left panel in Figure 2 illustrates the coefficients $\mathbf{\Theta}$ from a simple regression of estimated bidder fixed effects on year dummies. It is evident that, relative to the 1980s, the average bidder conducting acquisitions is of significantly lower fixed effect. The average firm-specific component declines in the early 1990s and remains between 1 and 2 percentage points lower than in the benchmark period. We add time-varying deal and bidder characteristics to the regression and report the coefficients $\mathbf{\Theta}$ on year dummies in the upper right panel of Figure 2. Controlling for these characteristics we find that the decline in the average bidder fixed effect over time is even more pronounced and reaches 3 percentage points by the year 2017. Further addition of industry dummies makes little difference to the estimated decline, with the results reported in the lower left panel of Figure 2.

[9]To reiterate, the firm fixed effect is estimated over the entire sample and, thus, does not change over time. What changes is the composition of bidders whose (constant) fixed effects make up the average fixed effect in a given year. The assumption of a stable bidder fixed effect is supported by the findings of Golubov, Yawson, and Zhang (2015), who show that period-specific fixed effects provide no additional explanatory power. In addition, as discussed in Section 2 above, less than a quarter of bidders is active beyond a ten-year period, preventing period-specific estimation for the majority of bidders.

3.4 A linear trend specification

Regressions reported in Table 4, Panel A provide a further check on the existence of a significant common time trend in acquirer returns. Here we replace the year dummies $\mathbf{Y}$ with a simple year counter, *Year trend*, which increases by one each year starting in 1990 (years 1981-1989 continue to serve as our baseline period). Thus, in this regression specification, we impose a linear relationship between acquirer returns and calendar time in years. Otherwise, we maintain the same four regression specifications as in Table 3. Therefore, the coefficient on the *Year trend* counter can be interpreted as the slope of the corresponding trend lines pictured in Figure 1. As shown in Column (1), when the regression excludes control variables, there is again no evidence of a significant linear trend in average acquirer returns.

In Column (2) of Table 4, we estimate the baseline year trend effect with control variables included. The coefficient on the *Year trend* variable becomes significant, but its economic magnitude is small: the average improvement in acquirer returns is 6 basis points per year, which translates into a 1.68 percentage point improvement by the end of our sample period (six basis points multiplied by 28 years over which the trend line is estimated, 1990-2017). This conclusion does not change when acquirer industry fixed effects are added in Column (3). In Column (4), we replace acquirer industry fixed effects with bidder fixed effects. Here the magnitude of the *Year trend* coefficient increases almost by a factor of three—to 17 basis points per year on average. Over the 28 year period to the end of our sample, this would imply an improvement of 4.76 percentage points, which is similar to the magnitude of the coefficient on the year dummy for 2017 pictured in the bottom right chart of Figure 1.

Finally, using the estimation procedure behind Panel A, in Panel B we estimate the slopes of the three annual trends lines for average bidder fixed effect plotted in Figure 2, by swapping the dependent variable for the estimated bidder fixed effect. We find statistically significant negative coefficients in all three cases, equal to -0.04, -0.12, and -0.12, respectively. This confirms that the composition of bidders has indeed changed towards lower fixed effect bidders over time. In sum, the increase in the common component of acquirer returns is offset by a decline in the average firm-specific component, which results in a largely flat unconditional average acquirer return.

In terms of robustness, in the Internet Appendix Table 3 we show that the baseline estimate of the upward time trend is largely invariant to alternative definitions of acquirer CAR, including after varying the event window to $[-1, +1]$, $[-2, +2]$, $[-5, +5]$, and to using market-adjusted returns and computing dollar gains and dollar gains scaled by deal value (i.e. NPV per dollar invested). In addition, the estimate holds up in more restrictive samples in terms of absolute and relative deal size and the number of deals per bidder. We also examine whether the conditional time trend in acquirer returns is broad-based or limited to certain subsets of the data by interacting the *Year trend* coefficient with various deal or bidder characteristics. We find that the conditional time trend in acquirer returns is broad-based: it applies equally well to deals involving listed and unlisted targets, cash and stock deals, focused and diversifying acquisitions, and domestic and cross-border deals. A significant portion of our bidders come from financial (17%) and high-tech (26%) industries.[10] Interestingly, the upward trend is more pronounced for bidders from the finance industry (banks, insurance firms, brokerage firms). To conserve space, these results are reported in Internet Appendix Table 4.

Finally, we consider whether the upward trend we document is simply an artifact of more timely pricing of event-induced gains by the stock market. First, we test whether the upward trend is observed for both value-creative and value-destroying transactions. We define a variable *Positive CAR*, which equals acquirer CAR when the latter is positive and zero otherwise. Similarly, we define a variable *Negative CAR*, which equals the acquirer CAR when the latter is negative, and zero otherwise. If more timely market pricing is the answer, we expect to find a negative coefficient on the *Year trend* variable when the dependent variable is *Negative CAR*. This is not the case: both *Positive CAR* and *Negative CAR* load positively on the time trend, as shown in Internet Appendix Table 5. Second, we estimate our results using a series of extended event windows, namely [−3, +21], [−3, +42], and [−3, +63]. More timely pricing of constant acquirer gains would imply that the upward time trend should dissipate as the event window is lengthened. Internet Appendix Table 5 shows that the opposite is true.

3.5 Simulation analysis

Are the two opposing trends we document related to each other? Or is the emergence of a positive common trend in a firm fixed effects specification simply an artifact of saturating the regression with high-dimensional fixed effects? To examine this important question, we test whether one can obtain the same year trend effect in a firm fixed effects specification, but where firm identifiers are shuffled across firms *within* year. This permutation of the data preserves the time dimension of our panel, such that each acquirer is observed the same number of times and in the same years as in the real data. However,

[10] High-tech industries are defined as in Loughran and Ritter (2004).

the permutation breaks the panel structure of the data whereby acquirers are assigned to deals conducted by *other* firms. If our finding of a strong positive trend in the common component of acquirer returns is indeed attributable to properly controlling for a composition effect, we should no longer find the same effect and observe a trend similar to that when firm fixed effects are omitted altogether.

We perform 1,000 such permutations of the data, each time repeating our regression specification from column (4) in Panel A of Table 4 and recording the coefficient on the *Year trend* variable. Figure 3 presents the distribution of the resulting coefficients across the permutations. The distribution of the *Year trend* coefficient is centered on 0.06, which coincides with the magnitude observed in column (3) in Panel A of Table 4 where no firm fixed effects are included in the regression at all. In fact, none of the 1,000 permutations results in a coefficient higher than 0.09, while the coefficient we obtain from the actual firm fixed effects specification is 0.17 as indicated by the vertical red line in Figure 3. Overall, the results of the simulation analysis confirm the tight link between the two opposing trends documented above.

3.6 Can sample truncation bias account for the two trends?

Since the observed acquisition histories of the earliest and the most recent bidders in our sample are likely incomplete, one may be wondering about the implications of truncation bias for our findings. In particular, consider a world with overlapping generations of bidders whose returns from acquisitions increase with experience. In that world, truncating acquisition histories at both ends of the sample would result in an upward (downward) bias in the average return of early (recent) bidders. Moreover, controlling for bidder composition would reveal an upward trend in returns within bidders. Can the two opposing trends we document be rationalized this way?

We argue that this not the case. First, the explanation above relies on increasing returns to acquisitions over a bidder's lifetime. The data are known to show the opposite: acquirer returns tend to *decline* over the course of acquisition sequences (see, e.g., Fuller, Netter, and Stegemoller (2002), Billett and Qian (2008)). This is true also in our sample. Second, in unreported analysis we re-estimate our results on a sample where each and every bidder is switched out (i.e. truncated) after its second deal, which puts all bidders on an equal footing. We find that our results become even more pronounced. We conclude that truncation of acquisition histories cannot account for the two trends we document.

4 A theory of bidder-specific merger synergies

The results thus far indicate that the average common component of acquirer returns has increased, while the average bidder-specific component has declined. These two trends counteract each other to produce largely stable unconditional average acquirer returns. How should one interpret these trends? At a high level, the results indicate that there has been a change in the composition of bidders over the sample period. Understanding the nature of this composition change is therefore key to decoding the patterns seen in the data. Golubov, Yawson, and Zhang (2015) undertake a comprehensive examination of firm-specific heterogeneity in acquirer returns and conclude that it likely represents latent bidder-specific resources—unique assets, business processes, or management skill unobservable to the econometrician—that the bidder contributes to the generation of synergies. While intuitive, the notion of bidder-specific synergies is largely new to the M&A literature. Therefore, to discipline any further conjectures, we first analyze the notion of bidder-specific synergies in the context of a simple takeover model. Let us preview a more formal analysis with some basic intuition.

In a typical merger, the two parties to a deal bring to the bargaining table resources that are deemed necessary to generate deal synergies. The uniqueness of these resources, in turn, determines that party's bargaining power. For example, deal synergies are mostly target-specific when a financially constrained target owns a unique technology (e.g., a patent) and the primary role of the bidder is to fund further technological developments. In this case, synergies are not specific to any particular bidder — so long as the bidder can provide the requisite funding. Competition among financially unconstrained bidders drives the bulk of deal synergies to the target shareholders. In contrast, suppose the bidder owns a unique downstream distribution network for the target's product. Absence of other potential bidders with a similarly cost-effective distribution network locks the target and the bidder in a bilateral, monopsonistic bargaining game. Synergy gains are now more bidder-specific, and the bidder has considerable power to extract a larger share of them. The key insight is that acquirer returns depend on the degree of the winning bidder's uniqueness in terms of the resources it brings to the deal.

Note that the same intuition regarding uniqueness applies to target firm resources: just like the presence of rival bidders increases the target's outside option, the availability of alternative synergistic targets increases the outside option of the bidder. For simplicity, we do not model target uniqueness and consider a setting that features a single target and one or more possible bidders. In what follows, we formalize our intuition in a simple theoretical framework linking announcement returns to total acquisition-induced synergies and the sharing of those gains between the winning bidder and the target. We then subject our framework's main prediction to rigorous empirical testing. Finally we use this framework to guide our interpretation of the time-series evolution of common and bidder-specific components of acquirer returns.

4.1 Formalization

Suppose that a merger deal between an acquirer A and the target T has just been announced to the market. The announcement drives the market's prior deal probability from zero to one—there is no market deal anticipation and a zero conditional risk of deal failure. Suppose also that the deal announcement does not alter the market's prior assessment of the stand-alone values of A (V_A) and T (V_T). The announcement reveals merger synergies totalling S dollars, generated by combining the resources of A with those of T. The acquirer A will receive the fraction $\theta \in (0,1)$ of the total synergies S, and the target T will receive the fraction $(1-\theta)$. Thus, the announcement returns to the two parties are given by $CAR_A = \theta S/V_A$ and $CAR_T = (1-\theta)S/V_T$.

Deals are agreed to as follows. Bidders do not undertake negative NPV investments. Hence, A is willing to offer up to the stand-alone value V_T plus the full value of synergies S (net of transaction costs), equivalent to $\theta \approx 0$. The target does not accept a bid that is less attractive than its outside option, i.e. its participation constraint is $V_T + (1-\theta)S \geq K$. Here, K is the value that T can extract from a combination with another bidder $\bar{A}$ (K is bounded from below by V_T if no other bidder exists). The alternative transaction generates synergies $\bar{S}$, and $\bar{A}$'s ability to pay is limited by the same participation constraint of non-negative NPV. It follows that the highest synergy bidder reaches a deal with the target; observing a deal between A and T implies that $S \geq \bar{S}$.

In this framework, the notion of bidder-specific synergies is reflected in the equilibrium synergy-sharing parameter θ. First, consider a case of synergies S that are not unique to any particular bidder: all bidders are perfect substitutes and a merger of T with any of them generates the same synergy $\bar{S} = S$. In this case, the target's outside option, $K = V_T + \bar{S}$, forces the successful bidder A to offer the full value of synergies S (net of transaction costs), resulting in $\theta \approx 0$. In contrast, suppose the synergies S are fully bidder-specific: the bidder A is so unique that only a merger of A and T creates any value, while a merger between $\bar{A}$ and T offers no synergies ($\bar{S} = 0$). Since no alternative bidders exist, the value of the target's outside option K is its stand-alone value V_T. Therefore, A bids $V_T + \epsilon$ (where ϵ is infinitesimal when bid revisions are costless), which the target ultimately accepts, resulting in $\theta \approx 1$. In intermediate cases, whereby $S > \bar{S} > 0$, A's offer is competed up to the valuation of the second-best bidder plus ϵ, resulting in $0 < \theta < 1$. The closer the second-best $\bar{S}/S$ is to 1, the closer to zero θ will be. Hence, the equilibrium outcome θ reflects the parties' bargaining power, as determined by the degree of substitutability between the winning bidder A and the second-best bidder $\bar{A}$.

We can formally express θ as $(1 - \bar{S}/S) \times k$, where $(1 - \bar{S}/S)$ is bidder uniqueness and $k \in [0, 1]$ is a constant parameter that governs the sharing of synergies over and above those of the second best, depending on the modelling choice.[11] The main prediction of this simple theory is that, holding other things equal, acquirer returns should increase with the degree of the winning bidder's uniqueness relative to the second best. In other words, when synergies are more bidder-specific, acquirer returns are higher. To our knowledge, this theoretical framework is one of the first attempts to model bargaining power in mergers and acquisitions. Below we develop four empirical proxies for bidder uniqueness to validate our theory.

4.2 Empirical testing of the framework

We would like to test whether a bidder's uniqueness in terms of ability to generate synergies with a given target has explanatory power for the cross-section of acquirer returns. This is a non-trivial task, because the extent to which deal synergies are specific to the winning bidder is inherently unobservable – counterfactual combinations and the associated synergies $\bar{S}$ are not observed. To overcome this challenge, we build on the idea that, in principle, identical firms are perfect substitutes as bidders and should therefore generate the same level of synergies with a given target. In other words, similarity between the observed (winning) bidder and all alternate buyers it must have outbid can be seen as a proxy for $\bar{S}/S$. Therefore, an empirical proxy for bidder uniqueness requires us to i) identify a set of alternate buyers (possible set of $\bar{A}$), and ii) measure the degree of similarity between the winning bidder and the second-best alternative from that set.

We identify the set of likely competing bidders for each deal in our sample as the set of all U.S. public firms at the time of deal announcement that satisfy two criteria: they come from the same 2-digit SIC

[11] To derive this, consider first a second-price auction, where the winning bidder makes an offer equal to $\bar{S}$ and gains an amount equal to $(S - \bar{S})$. Expressing this gain as a fraction of synergies S, we obtain $\theta = (1 - \bar{S}/S)$. If the target further captures a portion of the *surplus* synergies $(S - \bar{S})$, then A gains $(S - \bar{S}) \times k$, where $k \in [0, 1]$. Expressed as a fraction of synergies S, this gives $\theta = (1 - \bar{S}/S) \times k$. For example, $k = 1/2$ in a Nash bargaining game with full information.

industry as the winning bidder and are at least as large as the target (deal value) by market capitalization. In the very few cases where the winning bidder is smaller than the target, we use the size of the winning bidder as the lower bound constraint.[12] The intuition behind this approach is simple: we assume that the second-best use of the target firm's assets is in the same industry as the observed use (assumed first-best), and that various feasibility constraints prevent potential bidders from bidding for targets that are bigger than themselves (as is typically the case in the data). Thus, our set of potential rival bidders is tailored to each transaction on the basis of timing, industry, and size. A limitation of this approach, however, is that our set of alternate buyers excludes private and foreign firms.

To measure the degree of similarity between the winning bidder and each potential rival bidder, we use four different proxies that capture the commonality in stock returns, fundamentals, and product offerings of the two firms. Specifically, our four proxies are pairwise i) idiosyncratic stock return correlation, ii) sales growth correlation, iii) cash flow (ROA) correlation, and iv) textual similarity of product descriptions. The stock-return based proxy is inspired by the work of de Bodt, Eckbo, and Roll (2020), who use pairwise idiosyncratic stock return correlations as an all-encompassing measure of firm similarity to study how firms respond to competition shocks (e.g., by differentiating). Similar to their work, we use the correlation of daily stock return residuals from a two-factor model estimated over a one year period prior to deal announcement, with the market and industry returns (value-weighted 2-digit SIC industry portfolio) as factors.

Sales growth correlation and cash flow correlation proxies build on the same notion: similar firms should have highly correlated fundamentals. We compute these correlations using quarterly observations on industry-adjusted sales growth and industry-adjusted operating return on assets from Compustat over a five-year period prior to deal announcement. Our fourth, text-based proxy for bidder uniqueness builds on the work of Hoberg and Phillips (2010, 2016) who conduct textual analysis of product descriptions for the universe of Compustat firms starting from 1996. Specifically, they compute firm-by-firm cosine similarity for vectors characterizing product market language found in firms' 10-K filings. Once again, the idea behind this proxy for bidder uniqueness is that bidders with similar product portfolios should offer similar product market synergies with a given target. These data come directly from the authors.[13]

Having obtained these pairwise similarities between the winning bidder and each of its potential rival

[12] Naturally, targets of the deal in question are further purged from the set of possible competing bidders.

[13] We use the full TNIC file available from http://hobergphillips.tuck.dartmouth.edu/. We are grateful to Gerard Hoberg and Gordon Phillips for making these data available.

bidders, we select three rivals with the highest similarity as our proxy for the second-best bidder $\bar{A}$, and their average similarity as the theoretical $\bar{S}/S$.[14] The three-correlation based proxies for $\bar{S}/S$ are bounded between -1 and 1, but the negative values comprise only 2% and we set them equal to zero. The Hoberg-Phillips text-based similarity measure is bounded between 0 and 1 by construction. Our final measures of bidder uniqueness are equal to $(1 - \bar{S}/S)$, labelled *Uniqueness (ρ ret)*, *Uniqueness (ρ sales)*, *Uniqueness (ρ ROA)*, and *Uniqueness (HP)*.

Table 5 presents descriptive statistics and pairwise correlations for the four proxies. The average *Uniqueness (ρ ret)* is 0.80, implying that the average idiosyncratic stock return correlation between the bidder and top 3 potential rivals is 0.20. The mean *Uniqueness (ρ sales)* and *Uniqueness (ρ ROA)* are 0.33 and 0.30, respectively. Their values are lower, on average, because fundamentals tend to be more correlated than returns. The mean of the text-based proxy *Uniqueness (HP)* is 0.81, similar to that of the returns-based proxy. As one would expect for empirical measures of the same theoretical concept, the four proxies are positively correlated with each other. Not surprisingly, the highest pairwise correlation of 0.60 is between the two cash flow-based measures *Uniqueness (ρ sales)* and *Uniqueness (ρ ROA)*. Other pairwise correlations do not exceed 0.34.

Armed with these four proxies, we test our framework's main prediction, namely that acquirer returns should increase with bidder uniqueness. The results of these cross-sectional association tests are reported in Table 6. For each of the four bidder uniqueness proxies, we estimate three specifications that progressively add control variables: a simple univariate regression with year fixed effects, then adding our usual set of bidder- and deal-specific controls, and then further adding acquirer industry fixed effects. Using all four proxies, we find robust evidence that the degree of the winning bidder's uniqueness is associated with higher acquirer returns, regardless of the regression specification. The effects are not only statistically significant, but also economically large. Focusing on the most comprehensive specification in columns (3), (6), (9), and (12), we find that a one standard deviation change in bidder uniqueness is associated with 0.27-0.45 percentage points higher acquirer return. For comparison, the sample mean acquirer return is 0.97%. The coefficient estimates in this table provide another way to assess the economic magnitude of the effect. Recall that our proxies are bounded between 0 and 1, implying that the coefficient can be interpreted as the difference in acquirer returns between a fully substitutable bidder (uniqueness equal to

[14] We use the top 3 closest alternate buyers to account for noise in the estimation of the first-best similarity, as well as for potential constraints on the participation of any one firm in the contest for the target. Nevertheless, our results are robust to alternatives, such as top 1 and top 5 closest rival bidders.

0) and a completely unique one (uniqueness equal to 1). Focusing on the most complete specifications, this effect is between 1.43 to 4.77 percentage points difference in acquirer CAR. Thus, the effects of bidder uniqueness on acquirer returns are clearly of a first-order.

These results are in line with our theoretical framework above and constitute an important addition to the literature on the determinants of bidder takeover gains. Having established the validity of our theory of bidder-specific synergies, we now return to our time-series focus and use our theoretical framework to guide our interpretation of the evidence.

4.3 Interpreting the time-series evidence

In our analysis of the evolution of acquirer returns over time, none of the control variables in $\mathbf{X}$ directly measure the degree of bidder uniqueness in terms of generating deal synergies. Realistically, any attempt to proxy for the uniqueness of the bidder in question (including our own efforts above) will be necessarily incomplete. Indeed, in most cases such uniqueness is an unobservable firm-specific characteristic that is best captured by the bidder's identity itself. Bidders that systematically bring unique resources to the bargaining table will be characterized by systematically high acquirer returns, reflecting high average θ. Therefore, the variation in acquirer returns that is due to bidder uniqueness will be reflected in the econometric counterpart of a bidder's identity – bidder fixed effect estimate. This logic is behind the (speculative) interpretation of firm-specific heterogeneity in acquirer returns by Golubov, Yawson, and Zhang (2015) as reflecting bidder-specific synergies.

We now put this potential interpretation to an empirical test. If bidder fixed effects in acquirer returns reflect bidder uniqueness, then we would expect that the strong explanatory power of bidder uniqueness proxies documented above disappears when we control for bidder composition via bidder fixed effects. This is the test reported in Table 7. For each of the four proxies we report two regression specifications. In the first one (odd-numbered columns) we repeat the most complete regression specification from Table 6 on a sample without singleton bidders, and in the second one (even-numbered columns) we replace industry fixed effects with bidder fixed effects. For all four bidder uniqueness proxies, we find that their explanatory power for the cross-section of acquirer returns is fully subsumed by bidder fixed effects. All coefficients lose statistical significance, and the magnitudes of the coefficients go down towards zero. In other words, bidder composition effectively controls for bidder uniqueness.

In Table 8 we perform an even more direct test of the hypothesis that bidder composition effects in acquirer returns reflect bidder uniqueness. We do so by regressing the estimated fixed effects on bidder uniqueness proxies. These regressions are the same as those in Panel B of Table 4, except that now the main explanatory variable is each of our proxies for bidder uniqueness. We find that, regardless of the set of other regressors, bidder uniqueness proxies positively predict the estimated bidder fixed effect. The coefficients are statistically significant at the 1% level in 11 specifications out of the 12, and at the 5% level in the remaining one. The economic magnitudes are once again large. The difference between a fully substitutable bidder (uniqueness equal to 0) and a completely unique one (uniqueness equal to 1) in terms of the associated bidder fixed effect estimates is between 2.3% and 5.95%. For comparison, an interquartile range in the estimated bidder fixed effects is 6.92%.

The conclusion from the tests above is that bidder composition effects in acquirer returns reflect bidder uniqueness, or the bidder's average θ via its average $(1 - \bar{S}/S)$ across its deals. Our ability to characterize the composition effect allows us to interpret the time-series evidence. If bidder fixed effect estimates capture bidder uniqueness, then our evidence of declining average bidder fixed effects (Figure 2) suggests that bidders are becoming relatively less unique during our sample period, reflecting merger synergies that are less bidder-specific. In other words, whatever the source of merger synergies may be, they are becoming less unique to the winning bidder, which drives down the share of synergies it can extract and lowers acquirer returns.

Table 9 provides evidence that corroborates this particular interpretation of changing bidder composition. In this table we report regressions of our bidder uniqueness proxies on the time trend variable, conditional on all the other regressors in our full regression specifications. We find that the coefficient on the *Year trend* variable is negative and statistically significant for three out of the four proxies, namely *Uniqueness (ρ ret)*, *Uniqueness (ρ sales)*, and *Uniqueness (ρ ROA)*. The time-series coefficient is indistinguishable from zero for the *Uniqueness (HP)* proxy, but this measure is not available for half of our sample period, hence the coefficient reflects the change during the post-1996 period only. We conclude that bidder uniqueness has declined over time, and that the downward trending bidder-specific component of acquirer returns can be interpreted as a decline in bidder-specificity of merger synergies.

Finally, our theoretical framework and the empirical evidence above further help interpret the upward trending *common* component of acquirer returns. It is useful to restate that, in our framework, the acquirer return is $CAR_A = \theta S/V_A$. In other words, bidder announcement returns are a function of the total synergy pie S and the synergy-sharing parameter θ. If changing bidder composition reflects a temporal change in average θ, then the variation in acquirer CARs that remains *after* controlling for bidder composition should reveal the variation in S. Put differently, when θ declines, acquirer CAR should go down: pressure from rival bidders drives down the winning bidder's gains. Yet, this is not what we observe in the data. As shown in Figure 1 above, *unconditional* average acquirer returns are largely flat. It is as if acquirer returns have *not* declined on average to reflect the putative lower bidder uniqueness. The only way to rationalize this within our framework is by rising overall deal synergies, i.e. the decline in bidder uniqueness θ has been offset by an increase in total deal synergies S.

To test this conjecture, we resort to the public target subsample as a laboratory in which we can proxy for merger synergies S. As in Bradley, Desai, and Kim (1988), our first proxy for (scaled) merger synergies S is the combined firm abnormal return (bidder-target portfolio). In Column (1) of Panel A, Table 10, we regress the combined firm CAR on the time trend and a set of control variables that mimics the covariates used in Table 3, but we omit bidder fixed effects (replaced with industry fixed effects) to obtain estimates of unconditional changes over time.[15] The coefficient on the year trend indicator is positive and highly statistically significant, implying that combined firm gains (proxy for scaled S) have unconditionally increased. The coefficient magnitude of 0.10 suggests that the increase is 10 basis points per year, on average. That is, over a 28-year period since the 1980s, combined firm gains have increased by a cumulative 2.8 percentage points. Compared to the overall sample average of 1.79%, this increase is highly economically relevant.

To further buttress the interpretation of the rising common component in acquirer returns as reflecting an increase in merger synergies, we compare the respective coefficient magnitudes. Given the scaler of the combined CAR variable, the coefficient magnitude implies a 10 basis points increase in $S/(V_A + V_T)$ per year. We therefore rescale acquirer CAR to have the same scaler – combined firm market capitalization as opposed to acquirer market capitalization – and use it to re-run the conditional acquirer return regression (with bidder fixed effects) on the same sample. If our interpretation of the upward trend in the common component of acquirer returns as rising synergies is correct, we should find that the coefficient on the *Year trend* variable in this regression equals that in Column (1). We obtain a coefficient of 0.10 with a t statistic of 1.90. We are unaware of alternative interpretations that would predict these two different regressions to produce the same coefficient.

[15]The only modification in the set of controls is that the method of payment-listing status interactions are replaced with just the method of payment indicator since all targets are public. The cross-border indicator is further omitted because all deals are domestic.

In the rest of Panel A, we employ three additional fundamentals-based proxies for merger efficiency gains. Specifically, we measure the industry-adjusted change in the combined firm operating income in year three following completion of the deal relative to the weighted average of the bidder and target in the year prior to the merger. We scale operating income using three different scalers: total assets, sales, and the number of employees. Hence, the three variables can be interpreted as follows: Δ OI/Assets [−1, +3] is the percentage point change in the industry-adjusted operating return on assets, Δ OI/Sales [−1, +3] is the percentage point change in the industry-adjusted operating margin, and Δ OI/Emp. [−1, +3] is the industry-adjusted change in operating income per employee (in $ thousand).

The results in Column (2) indicate that the incremental improvement in the merged firm's industry-adjusted operating return on assets over time is 0.06 percentage points per year (an improvement of 1.68 percentage from 1980s to the end of 2017). Column (3) shows that the incremental improvement over time in the combined firm's industry-adjusted operating margin is 0.08 percentage points per year (an improvement of 2.24 percentage from 1980s to the end of 2017). Finally, Column (4) shows that the incremental temporal improvement in the merged entity's operating income per employee is $1.03 thousand per year (an improvement of $28.9 thousand from 1980s to the end of 2017). These results further corroborate our interpretation of the rising common component of acquirer returns as resulting from an increase in merger synergies.

We obtain our final confirmatory evidence from target firm abnormal returns. In our framework, target firm return is $CAR_T = (1-\theta)S/V_T$. Thus, targets benefit from declining bidder uniqueness, as reflected in θ, as well as from the rise in S, though the latter depends on the specific setup.[16] Therefore, we would expect target firm returns to have increased over time. We test this prediction in Panel B of Table 10. In Column (1) we regress the 7-day target firm announcement return, Target CAR [−3, +3], on the *Year trend* variable, and the same set of control variables as in Panel A. The time-series coefficient is positive and marginally statistically significant, with the magnitude of 0.20 indicating a 20 basis points improvement in target CAR per year.

Our framework demonstrates the target CAR is scaled by V_T, and V_T has undoubtedly increased over time, potentially biasing the coefficient on the *Year trend* variable downward. Therefore, in Column (2)

[16] Recall that, in our framework, the winning bidder has to outbid the second-best bidder $\bar{A}$ and therefore offers a dollar premium equal to at least $\bar{S}$. Whether the target extracts a price higher than that depends on the model setup, as summarized by the parameter k in the theoretical framework above. When the target does not share in the surplus synergies $(S-\bar{S})$, the target return can be written as $CAR_T = (1-\theta)S/V_T = \bar{S}/V_T$, which is independent of deal synergies S.

we additionally control for the same set of target firm characteristics as those of the acquirer, including target size. We find that the magnitude of the time trend coefficient increases to 0.34 and statistical significance improves to 1% level. To ensure that the observed increase in target returns is not simply due to lower run-ups and a more pronounced reaction at the announcement (with the overall return remaining constant), in Column (3) we repeat the test but this time include the run-up period in the computation of the target firm return, Target CAR [−42, +3]. The coefficient magnitude drops slightly, but remains statistically significant at 10% level. Finally, to ensure that the temporal increase in target announcement returns does not simply reflect greater expected probability of deal completion, in Column (4) we exclude withdrawn deals and further extend the event window to 3 days following the completion date, Target CAR [−42, Compl +3]. There is little change in the estimated time trend effect when potential temporal differences in completion expectations are taken into account.

Overall, the results of the tests reported in this section are consistent with a world in which merger synergies have increased over time, but have become less bidder-specific. The two forces counteract each other to produce largely constant bidder gains over time. In the remainder of the paper we briefly explore potential economic drivers of declining bidder uniqueness and rising merger synergies. This also provides an opportunity to discuss our results in the context of the M&A and broader finance literature.

5 The drivers of declining bidder uniqueness and rising synergies

Our findings that overall synergies are now higher but less bidder-specific naturally raise questions about the underlying economic drivers of these changes. What is the source of rising synergies? And why have they become less bidder-specific, i.e. why has bidder uniqueness declined? While we do not provide definitive answers to those questions, we do offer some exploratory evidence that may help guide future work on these questions. We first consider why bidder uniqueness may have declined, and conclude with an examination of the source of rising synergies.

5.1 Why has bidder uniqueness declined?

Generally speaking, generating synergies requires a combination of various resources coming from the target and the acquirer. One possible explanation for the decline in bidder uniqueness is that bidders today contribute inputs that are more commonly available in the economy and thus no longer represent a unique resource. Below we provide some suggestive evidence of this evolution, focusing on two key inputs: knowledge capital (e.g. patents, expertise, innovation), and financial capital (e.g. cash, financing capacity).

We focus on those inputs for two reasons. First, studies of mergers and acquisitions have identified them as a source of merger synergies (see, e.g. Erel, Jang, and Weisbach (2015) for financing power and Bena and Li (2014) for innovation capabilities). Second, the broader finance literature suggests that there have been temporal shifts in their importance and/or availability. For instance, studies on intangible capital suggest that investment in innovation contributes to differentiation and is becoming more important over time (Hoberg and Phillips (2016), Peters and Taylor (2017)). In contrast, studies of financing markets suggest that financing is now more commonly available due to various financial reforms and innovations, such as banking deregulation (Jayaratne and Strahan (1996)), advent of junk bond financing (Lemmon and Roberts (2010)), and securitization (Berg, Streitz, and Wedow (2019)). Could it be that bidders are falling behind in terms of hard-to-replicate innovative assets, thereby losing their differentiation? And could it be that deep-pocketed bidders no longer possess a unique resource?

To answer these questions we study all U.S. non-financial firms from Compustat, distinguishing between the population of bidders and all other firms. A firm is considered to be a bidder if it will engage in one ore more M&A deals during the following 12 months according to our sample from SDC, or if it records acquisition spending in its cash flow statement over the next fiscal year greater than \$1M. Non-bidders are all other firms in Compustat in that year. We evaluate and compare the financing flexibility of bidders vis-a-vis non-bidders. Our measure of financial flexibility rests on the idea that constrained firms rely more heavily on internal cash flow to finance investment, and that observing greater model R^2 when adding cash flow to a regression of investment on Tobin's Q is indicative of financing constraints. Every year, we regress investment on Q for the two cross-sections and capture the impact of adding internal cash flow to the R^2 of the regression. Formally, we calculate this impact as $(R^2_{Q,CF} - R^2_Q)/(1 - R^2_Q)$ where $R^2_Q(R^2_{Q,CF})$ is the R^2 of the regression without (with) cash flow.

Figure 4 shows the evolution of this incremental R^2 for bidders and non-bidders. This graphic reveals three main patterns. First, bidders (solid blue line) are generally *less* financially constrained than firms that do not undertake acquisitions (dashed red line), consistent with bidders being generally deep-pocketed. Second, there has been a general increase in financial flexibility. Financing constraints have decreased modestly for bidders, and significantly so for non-bidders. Third, by the end of our sample period financing constraints of bidders and non-bidders have converged to the same level. In other words, bidders are no longer different from other firms in the economy in terms of their financial flexibility. Overall, Figure 4 suggests that firms making acquisitions in the early part of the sample had a comparative advantage in terms of access to financing, but this comparative advantage no longer exists today.

Next we investigate the level of hard-to-replicate knowledge capital for bidders and the average non-bidder in the economy. Our measure here comes from Peters and Taylor (2017) and represents the percentage of knowledge capital (capitalized R&D investment) in total capital of the firm, both tangible and intangible. We compute and plot the average percentage of knowledge capital every year for the two groups of firms: bidders (solid blue line) and non-bidders (dashed red line). Figure 5 presents the results of this analysis. We find that bidders, on average, tend to have *less* knowledge capital than the others do, suggesting that firms making acquisitions are lagging behind in terms of innovation. More importantly, we find that the fraction of knowledge capital that bidders have prior to making a bid has increased, but not by enough to offset the gap relative to the average firm. This gap has in fact widened considerably over the sample period, suggesting an erosion in terms of the ability to contribute hard-to-replicate assets to the merger.

Overall, the results reported here are consistent with the notion that bidding firms are losing their comparative advantage in terms of unique resources. They have fallen behind the average non-bidding firm in terms of innovation, while non-bidders have caught up with bidders in terms of financing power.

5.2 Why have merger synergies increased?

Finally, we examine a number of hypotheses for why merger synergies may have increased. Since our analysis shows that the upward trend is broad-based, we focus on economic hypotheses that could predict a market-wide improvement in overall takeover gains over time. These hypotheses span learning and age effects, better corporate governance, trends in industry concentration, and changes in the market for M&A advisory. Interestingly, the results of this analysis are notable for what does *not* work. We provide only a brief summary here; detailed discussion can be found in the Internet Appendix.

First, improved deal-making over time by repeat acquirers could be consistent with a learning-by-doing effect: bidders could be learning how to select suitable acquisition targets and integrate them. While the literature on serial acquirers documents a declining trend in acquirers' cumulative abnormal returns in successive acquisitions (Fuller, Netter, and Stegemoller, 2002; Billett and Qian, 2008; Aktas, de Bodt, and Roll, 2013), to our knowledge these studies do not control for bidder composition. It is thus possible that bidder composition has previously obscured the learning effect in the data. However, as shown in Internet Appendix Tables 6 and 7, we find no evidence that the upward trend in the common component of acquirer returns is related to deal experience. We also consider whether firm age—collinear with the time trend in a firm fixed effects specification—has any explanatory power. It does not. The takeaway is that the upward trend in the common component of acquirer returns is a calendar time effect, not an experience or an age effect.

Second, the literature points to a potential for better corporate governance to improve acquisition decisions, increasing the fraction of deals undertaken for efficiency-seeking reasons.[17] Incidentally, there has been a trend in pertinent governance characteristics: a decline in the frequency of staggered boards (Cremers, Litov, and Sepe, 2017), an increase in board independence (Duchin, Matsusaka, and Ozbas, 2010), increased equity-based compensation (Edmans, Gabaix, and Jenter, 2017), and a rise in institutional ownership (Lewellen, 2011). Nevertheless, as shown in Internet Appendix Table 8, we fail to find support for the hypothesis that changes in these governance characteristics at the firm level can explain the upward trend in the common component of acquirer returns. It is still possible that improved governance is at work, but in ways not amenable to large sample testing (e.g. through increased shareholder activism (Brav, Jiang, Ma, and Tian, 2018)).

Third, Gutiérrez and Philippon (2017) and Grullon, Larkin, and Michaely (2019) show that U.S. industries have become more concentrated over time, prompting us to consider market power effects (either upstream or downstream) as a potential source of increased merger gains. The trend toward higher industry concentration is of further interest because the degree of product market competition may constrain corporate mismanagement (Giroud and Mueller, 2010, 2011). Since firms in highly competitive industries operate with thin profit margins, there is more room for mismanagement of free cash flow in monopolistic industries. We perform two sets of tests that lead us to reject this potential link. First, in Internet Appendix Table 9, we find no corresponding time trends in the market reaction of rival, customer, and supplier firms. Second, in Internet Appendix Table 10, various measures of industry concentration fail to explain the upward trend we document.

Finally, several studies point to the importance of financial advisors in mergers and acquisitions

[17]See, e.g., Datta, Iskandar-Datta, and Raman (2001) for equity-based compensation, Masulis, Wand, and Xie (2007) for antitakeover provisions, and Dahya, Golubov, Petmezas, and Travlos (2019) for board independence.

(Servaes and Zenner, 1996; Rau, 2000; Kale, Kini, and Ryan, 2003; Golubov, Petmezas, and Travlos, 2012). We examine the possibility that changes in the market for M&A advisors have affected the quality of M&A deals they propose and execute. For example, during the 1980s and 1990s, major investment banking houses converted from partnerships to corporations and went public (Morrison and Wilhelm, 2008). The industry has also seen mergers between banks and securities firms during the late 1990s and early 2000s, and the entry of "boutique" M&A advisors (Song, Wei, and Zhou, 2013). During this industry transformation, traditional investment banking relationships have become increasingly transactional, with acquirers switching advisors more frequently (Corwin and Stegemoller, 2014). In Internet Appendix Table 11 and Internet Appendix Figure 1, we find some limited evidence that the composition of advisors can explain a small portion of the upward trending common component of acquirer returns – as if bidders are gravitating towards higher value-added advisors over time. However, the upward trend is also present in deals that likely involved no advisors.

Overall, the source of rising merger synergies eludes us. That said, to the extent that merger synergies arise from economies of scale and scope, our results are consistent with a world in which these economies have increased. For instance, in their analysis of disappearing IPOs in the U.S., Gao, Ritter, and Zhu (2013) argue that the importance of economies of scale and scope has increased over time, making it more profitable for young firms to sell out to corporate buyers. Our evidence on rising merger synergies is consistent with that hypothesis.

6 Conclusion

The seemingly unchanged average acquirer returns over the last four decades mask two fundamental shifts in the market for corporate control. Controlling for bidder composition, we find that acquirer returns have actually increased by as much as five percentage points relative to the 1980s. This increase is broad-based: it is equally present in deals involving public and private targets, cash and stock deals, diversifying and focused acquisitions, and domestic and cross-border deals. Working against this increase, the average bidder-specific component of acquirer returns has declined.

We develop and test a single, unifying theoretical framework of bidder-specific merger synergies that helps interpret our findings of time-series and composition effects in acquirer returns. In our theory, acquirer returns increase with the degree of the winning bidder's uniqueness in terms of generating deal synergies relative to the second-best alternate buyer. We develop empirical proxies for bidder uniqueness and find strong support for our prediction in the data. Bidder composition effects we document are related to bidder uniqueness. We argue that the time-series evidence is consistent with declining bidder uniqueness, whereby merger synergies are becoming less bidder-specific. This trend has been offset by rising total deal synergies, thereby keeping acquirer returns flat over time.

We also undertake a search for the economic drivers of declining bidder uniqueness and rising merger synergies. We find that bidders have fallen behind in terms of the uniqueness of the resources they bring into the deal: financing power is no longer limited to bidders, and they are now lagging other firms in terms of hard-to-replicate innovative assets. The drivers of rising synergy gains elude us, as we find no support for channels such as learning, improved corporate governance, or increased industry concentration. The source of rising synergies remains a puzzle to be addressed in future research.

References

Aktas, Nihat, Eric de Bodt, and Richard Roll, 2013, Learning from repetitive acquisitions: Evidence from the time between deals, *Journal of Financial Economics* 108, 99–117.

Alexandridis, G., N. Antypas, and N. Travlos, 2017, Value creation from M&As: New evidence, *Journal of Corporate Finance* 45, 632–650.

Bai, Jennie, Thomas Phillipon, and Alexi Savov, 2016, Have financial markets become more informative?, *Journal of Financial Economics* 122, 625–654.

Bena, Jan, and Kai Li, 2014, Corporate innovations and mergers and acquisitions, *Journal of Finance* 69, 1923–1960.

Berg, Tobias, Daniel Streitz, and Michael Wedow, 2019, Credit supply and (in)organic growth, Working Paper, Frankfurt School of Finance and Management, Copenhagen Business School, and the European Central Bank.

Betton, Sandra, B. Espen Eckbo, Rex Thompson, and Karin S. Thorburn, 2014, Merger negotiations with stock market feedback, *Journal of Finance* 69, 1705–1745.

Betton, Sandra, B. Espen Eckbo, and Karin S. Thorburn, 2008, Corporate takeovers, in B. E. Eckbo, ed.: *Handbook of Corporate Finance: Empirical Corporate Finance*, vol. 2 . chap. 15, pp. 291–430 (Elsevier/North-Holland).

Billett, Matthew T., and Yiming Qian, 2008, Are overconfident CEOs born or made? Evidence of self-attribution bias from frequent acquirers, *Management Science* 54, 1037–1051.

Bradley, M, A Desai, and E H Kim, 1988, Synergistic gains from corporate acquisitions and their division between the stockholders of target and acquiring firms, *Journal of Financial Economics* 21, 3–40.

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, 2018, How does hedge fund activism reshape corporate innovation?, *Journal of Financial Economics* 130, 237–264.

Corwin, Shane A., and Mike Stegemoller, 2014, The changing nature of investment banking relationships, Working Paper, University of Notre Dame and Baylor University.

Cremers, Martijn K. J., Lubomir P. Litov, and Simone M. Sepe, 2017, Staggered boards and long-tern firm value, revisited, *Journal of Financial Economics* 126, 422–444.

Dahya, Jay, Andrey Golubov, Dimitris Petmezas, and Nickolaos G. Travlos, 2019, Governance mandates, outside directors, and acquirer performance, *Journal of Corporate Finance* 59, 218–238.

Datta, Sudip, Mai Iskandar-Datta, and Kartik Raman, 2001, Executive compensation and corporate acquisition decisions, *Journal of Finance* 56, 2299–2336.

de Bodt, Eric, B. Espen Eckbo, and Richardl Roll, 2020, Corporate rivalry and return comovement, Working Paper, NHH, Dartmouth College, and California Institute of Technology.

Doidge, Craig, G. Andrew Karolyi, and Rene M. Stulz, 2017, The US listing gap, *Journal of Financial Economics* 123, 464–487.

Duchin, Ran, John G. Matsusaka, and Oguzhan Ozbas, 2010, When are outside directors effective?, *Journal of Financial Economics* 96, 195–214.

Eckbo, B. Espen, and Markus Lithell, 2020, The merger-adjusted US listing gap, Working Paper, Dartmouth College and the Norwegian School of Economics.

Eckbo, B. Espen, Tanakorn Makaew, and Karin S. Thorburn, 2018, Are stock-financed takeovers opportunitstic?, *Journal of Financial Economics* 128, 443–465.

Eckbo, B. Espen, and Karin S. Thorburn, 2000, Gains to bidder firms revisited: Domestic and foreign acquisitions in Canada, *Journal of Financial and Quantitative Analysis* 35, 1–25.

Edmans, Alex, Xavier Gabaix, and Dirk Jenter, 2017, Executive compensation: A survey of theory and evidence, in Benjamin E. Hermalin, and Michael S. Weisbach, ed.: *Handbook of the Economics of Corporate Governance*, vol. 1 . chap. 7, pp. 383–539 (Elsevier, Amsterdam).

Erel, Isil, Yeejin Jang, and Michael S. Weisbach, 2015, Do acquisitions relieve target firms financial constraints?, *The Journal of Finance* 70, 289–328.

Faccio, Mara, John J. McConnell, and David Stolin, 2006, Returns to acquirers of listed and unlisted targets, *Journal of Financial and Quantitative Analysis* 41, 197–220.

Fama, Eugene F., and Kenneth R. French, 2004, New lists: Fundamentals and survival rates, *Journal of Financial Economics* 73, 229–269.

Fuller, Kathleen, Jeffrey Netter, and Mike Stegemoller, 2002, What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions, *Journal of Finance* 57, 1763–1793.

Gao, Xiaohui, Jay R. Ritter, and Zhongyan Zhu, 2013, Where have all the IPOs gone?, *Journal of Financial and Quantitative Analysis* 48, 1663–1692.

Gillan, Stuart, and Laura Starks, 2007, The evolution of shareholder activism in the united states, *Journal of Applied Corporate Finance* 19, 55–73.

Giroud, Xavier, and Holger M. Mueller, 2010, Does corporate governance matter in competitive industries?, *Journal of Financial Economics* 95, 312–331.

———, 2011, Corporate governance, product market competition, and equity prices, *Journal of Finance* 66, 563–600.

Golubov, Andrey, Dimitris Petmezas, and Nickolaus G. Travlos, 2012, When it pays to pay your investment banker: New evidence on the role of financial adviosors in M&As, *Journal of Finance* 67, 271–311.

Golubov, Andrey, Alfred Yawson, and Huizhong Zhang, 2015, Extraordinary acquirers, *Journal of Financial Economics* 116, 314–330.

Grullon, Gustavo, Yelena Larkin, and Roni Michaely, 2019, Are US industries becoming more concentrated?, *Review of Finance* forthcoming.

Gutiérrez, Germán, and Thomas Philippon, 2017, Declining competition and investment in the US, Working Paper, New York University.

Hoberg, Gerard, and Gordon Phillips, 2010, Product market synergies and competition in mergers and acquisitions: A text-based analysis, *Review of Financial Studies* 23, 3773–3811.

———, 2016, Text-based network industries and endogenous product differentiation, *Journal of Political Economy* 124, 1423–1465.

Jayaratne, Jith, and Philip E. Strahan, 1996, The finance-growth nexus: Evidence from bank branch deregulation, *Quarterly Journal of Economics* 11, 639–670.

Jensen, Michael C., and Richard S. Ruback, 1983, The market for corporate control, *Journal of Financial Economics* 11, 5–50.

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

Krueger, Philipp, Augustin Landier, and David Thesmar, 2015, The WACC fallacy: The real effects of using a unique discount rate, *Journal of Finance* 70, 1253–1285.

Lemmon, Michael, and Michael R. Roberts, 2010, The response of corporate financing and investment to changes in the supply of credit, *Journal of Financial and Quantitative Analysis* 45, 555–587.

Lewellen, Jonathan, 2011, Institutional investors and the limits of arbitrage, *Journal of Financial Economics* 102, 62–80.

Loughran, Tim, and Jay R. Ritter, 2004, Why has IPO underpricing changed over time?, *Financial Management* 33, 5–37.

Maloney, M. T., R. E. McCormick, and M. L. Mitchell, 1993, Managerial decision making and capital structure, *Journal of Business* 66, 189–217.

Masulis, Ronald W., Cong Wand, and Fei Xie, 2007, Corporate governance and acquirer returns, *Journal of Finance* 62, 1851–1889.

Moeller, Sara B., Frederik P. Schlingemann, and René M. Stulz, 2004, Firm size and the gains from acquisitions, *Journal of Financial Economics* 73, 201–228.

——— , 2005, Wealth destruction on a massive scale? A study of acquiring firm returns in the recent merger wave, *Journal of Finance* 60, 757–782.

Morrison, Alan D., and William J. Wilhelm, 2008, The demise of investment banking partnerships: Theory and evidence, *Journal of Finance* 63, 311–350.

Netter, Jeffry, Michael Stegemoller, and Modupe Wintoki, 2011, Implications of data screens on merger and acquisition analysis: A large sample study of mergers and acquisitions from 1992-2009, *Review of Financial Studies* 24, 2242–2285.

Peters, Ryan H., and Lucian A. Taylor, 2017, Intangible capital and the investment-q relation, *Journal of Financial Economics* 123, 251 – 272.

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

Roll, R, 1986, The hubris hypothesis of corporate takeovers, *Journal of Business* 59, 437–467.

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

Schneider, Christoph, and Oliver G. Spalt, 2019, On the use of proxy variables in finance: Why does size matter for bidder announcement returns?, Working Paper, Tilburg University.

Servaes, Henri, and Marc Zenner, 1996, The role of investment banks in acquisitions, *Review of Financial Studies* 9, 787–815.

Song, Weihong, Jie Wei, and Lei Zhou, 2013, The value of boutique financial advisors in mergers and acquisitions, *Journal of Corporate Finance* 20, 94–114.

Travlos, Nickolaos G., 1987, Corporate takeover bids, method of payment, and bidding firms' stock returns, *Journal of Finance* 42, 943–963.

Figure 1: Evolution of average acquirer announcement returns

The four panels plot the coefficients **S** for the vector **Y** of year dummies corresponding to the CAR regressions reported in Table 3, as follows:

$$
\begin{aligned}
&\text{Top left panel:} && CAR[-3,+3]_i && = \alpha + \mathbf{SY_i'} + \epsilon_i \\
&\text{Top right panel:} && CAR[-3,+3]_i && = \alpha + \mathbf{SY_i'} + \mathbf{\Gamma X_i'} + \epsilon_i \\
&\text{Bottom left panel:} && CAR[-3,+3]_i && = \alpha + \mathbf{SY_i'} + \mathbf{\Gamma X_i'} + IndFE + \epsilon_i \\
&\text{Bottom right panel:} && CAR[-3,+3]_i && = \alpha + \mathbf{SY_i'} + \mathbf{\Gamma X_i'} + BidderFE + \epsilon_i.
\end{aligned}
$$

The vector **Y** includes indicator variables for deal announcement years from 1990 to 2017, with all of the 1980s as the omitted category. Thus, coefficients **S** estimate the change in average acquirer CAR $[-3, +3]$ relative to acquisitions announced during the 1981-1989 period. Grey-shaded areas correspond to a 99% confidence interval.

Figure 2: Evolution of average bidder fixed effects

The three sub-figures plot the coefficients $\mathbf{\Theta}$ for the vector $\mathbf{Y}$ from a regression of estimated bidder fixed effects on year dummies, as follows:

$$\begin{aligned}
&\text{Top left panel:} && \widehat{BidderFE}_i &&= \alpha + \mathbf{\Theta}\mathbf{Y_i'} + \epsilon_i \\
&\text{Top right panel:} && \widehat{BidderFE}_i &&= \alpha + \mathbf{\Theta}\mathbf{Y_i'} + \mathbf{\Gamma}\mathbf{X_i'} + \epsilon_i \\
&\text{Bottom left panel} && \widehat{BidderFE}_i &&= \alpha + \mathbf{\Theta}\mathbf{Y_i'} + \mathbf{\Gamma}\mathbf{X_i'} + IndFE + \epsilon_i.
\end{aligned}$$

The vector $\mathbf{Y}$ includes indicator variables for deal announcement years from 1990 to 2017, with all of the 1980s as the omitted category. Thus, coefficients $\mathbf{\Theta}$ estimate the change in the average bidder fixed effect for all bidders conducting deals in a given year relative to the average bidder fixed effect during the 1981-1989 period. Bidder fixed effects are estimated in a regression specification reported in column (4) of Table 3. Grey-shaded areas correspond to a 99% confidence interval.

Figure 3: Permutation analysis: Randomizing acquirer IDs

The histogram presents the distribution of the coefficient on the *Year trend* variable in a firm fixed effects specification across the permutations. One thousand permutations of the data are performed: each time the acquiring firm identifiers are randomly shuffled across firms within a given year. The vertical red line indicates the coefficient on the *Year trend* variable in the firm fixed effects specification run on the actual data.

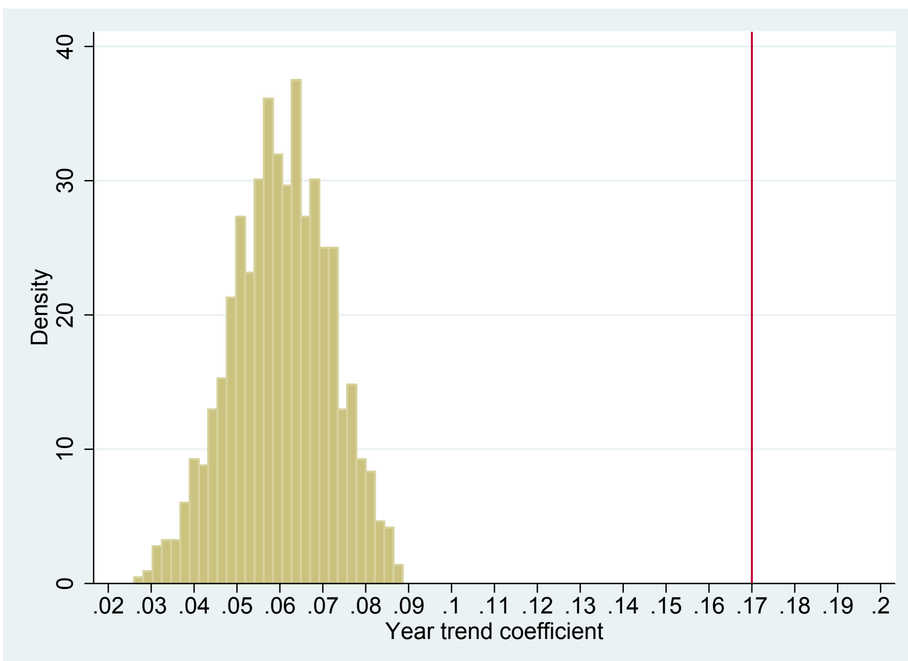


Figure 4: Is bidder financing power no longer a unique resource?

The graph plots the incremental R^2 effect of adding a measure of cash flow to annual cross-sectional investment-to-Q regressions run separately for bidders and non-bidders over time. Bidders (solid blue line) are all firms conducting an acquisition that satisfies our sample selection criteria, as well as any firm that reports positive acquisition CAPEX in its cash flow statement in Compustat in a given year. Non-bidders (red dashed line) are all other firms in Compustat in that year.

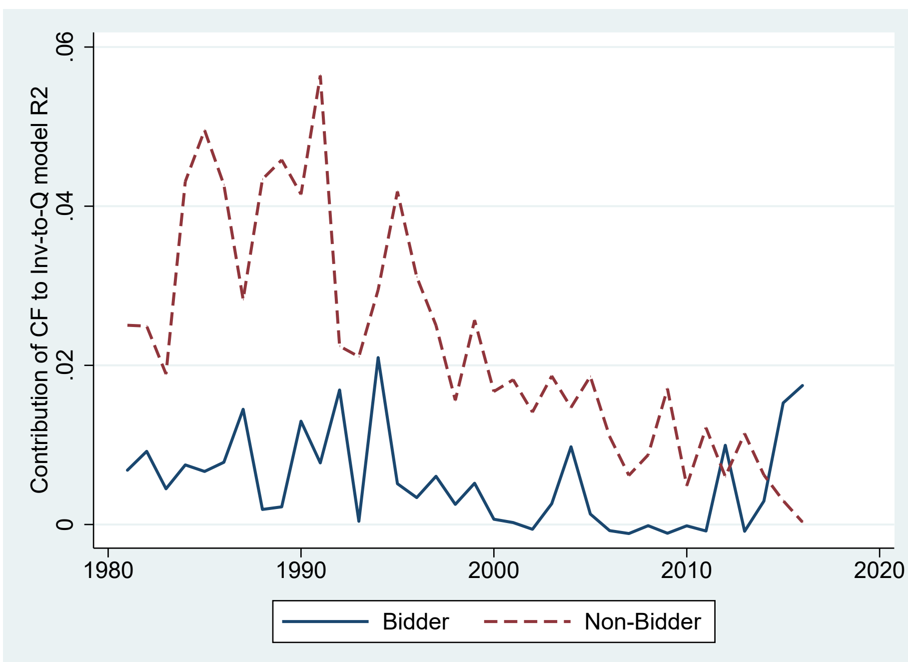


Figure 5: Are bidders falling behind in terms of knowledge capital?

The graph plots the average percentage of knowledge capital to total capital (R&D stock based on perpetual inventory method divided by the sum of tangible and intangible capital) following Peters and Taylor (2017) separately for bidders and non-bidders over time. Bidders (solid blue line) are all firms conducting an acquisition that satisfies our sample selection criteria, as well as any firm that reports positive acquisition CAPEX in its cash flow statement in Compustat in a given year. Non-bidders (red dashed line) are all other firms in Compustat in that year. Grey-shaded areas correspond to a 99% confidence interval.

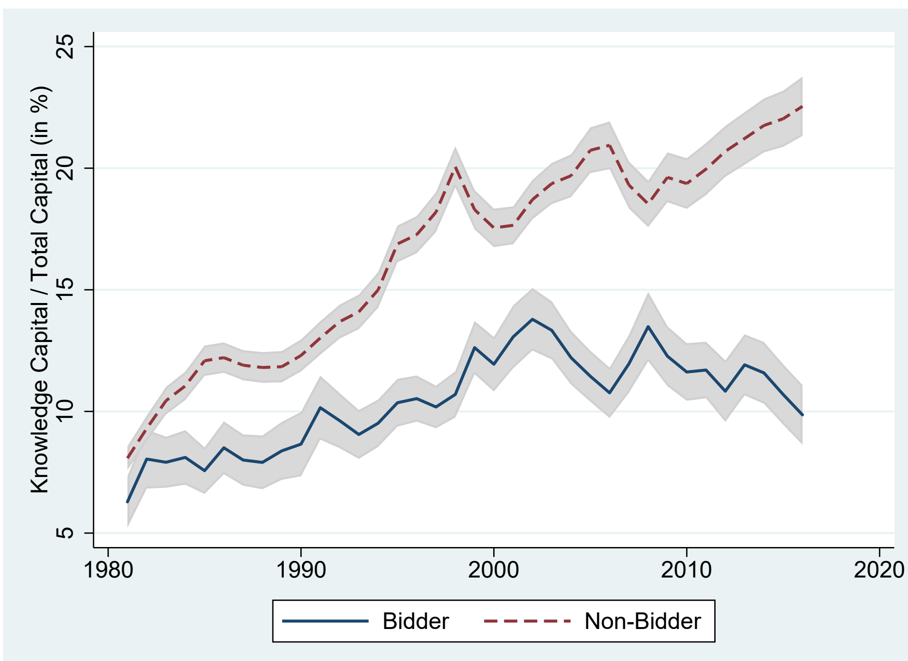


Table 1: M&A sample: panel structure

The table describes the panel structure of our sample of U.S. M&A deals over the period 1981-2017. All bidders are U.S. public firms with common stock listed on NYSE, Nasdaq, or Amex with a market capitalization of at least $1 million and a stock price of at least $1. All targets are either U.S. or foreign public, private, and subsidiary firms. Deals with missing transaction values, deals worth less than U.S. $1 million or smaller than 1% of acquirer market capitalization, and deals falling within 5 days of a quarterly earnings announcement are excluded. Panel A presents the distribution of the number of deals per bidder. Panel B presents the distribution of the mean time between successive deals, as well as the time between first and last deal of a given bidder.

Panel A: Number of deals per bidder

Deals per bidder	**N of bidders**	**%**	**Cum %**	**N of deals**	**%**	**Cum %**
2	1,890	35.29	35.29	3,780	16.05	16.05
3	1,081	20.18	55.47	3,243	13.77	29.82
4	679	12.68	68.15	2,716	11.53	41.35
5	464	8.66	76.81	2,320	9.85	51.20
6	317	5.92	82.73	1,902	8.08	59.27
7	233	4.35	87.08	1,631	6.92	66.20
8	172	3.21	90.29	1,376	5.84	72.04
9	124	2.32	92.61	1,116	4.74	76.78
10	80	1.49	94.10	800	3.40	80.18
11	63	1.18	95.28	693	2.94	83.12
12	69	1.29	96.56	828	3.52	86.63
13	39	0.73	97.29	507	2.15	88.79
14	30	0.56	97.85	420	1.78	90.57
15	30	0.56	98.41	450	1.91	92.48
16	13	0.24	98.66	208	0.88	93.36
17	11	0.21	98.86	187	0.79	94.16
18	8	0.15	99.01	144	0.61	94.77
19	12	0.22	99.23	228	0.97	95.74
20+	41	0.77	100.00	1,004	4.26	100.00
Total	5,356	100.00		23,553	100.00	

Panel B: Distribution of time between deals of a given bidder

	Mean	**10 pctl.**	**25 pctl.**	**Median**	**75 pctl.**	**90 pctl.**
Mean t between deals	32.00	2.27	6.50	16.77	40.43	81.90
t between 1st and last deals	85.20	7.27	19.13	53.52	128.48	209.33

Table 2: Acquirer announcement returns by year

The table presents average acqurier returns and deal activity by year for a sample of U.S. M&A deals over the period 1981-2017. All bidders are U.S. public firms with common stock listed on NYSE, Nasdaq, or Amex with a market capitalization of at least $1 million and a stock price of at least $1. All targets are either U.S. or foreign public, private, and subsidiary firms. Deals with missing transaction values, deals worth less than U.S. $1 million or smaller than 1% of acquirer market capitalization, and deals falling within 5 days of a quarterly earnings announcement are excluded.

Year	Mean CAR	Median CAR	N of Deals	Mean Deal Val.	Median Deal Val.	Total Deal Val.
1981	-1.82	-1.50	213	481.79	64.28	102,621
1982	0.49	0.16	254	246.93	51.81	62,719
1983	0.16	-0.18	355	201.52	58.41	71,541
1984	0.46	-0.28	390	429.60	53.83	167,543
1985	-0.39	-0.79	250	904.11	264.11	226,027
1986	0.77	0.11	336	539.15	148.42	181,156
1987	1.20	-0.12	309	564.13	141.68	174,318
1988	0.58	-0.31	324	463.45	129.38	150,159
1989	0.04	-0.30	406	546.43	83.58	221,850
1990	0.07	-0.29	376	276.86	44.28	104,101
1991	1.63	0.57	389	216.08	41.15	84,055
1992	2.47	1.00	595	167.20	34.08	99,485
1993	1.57	0.71	781	349.07	34.14	272,622
1994	1.48	0.64	1,042	245.23	38.29	255,528
1995	0.84	0.11	1,085	346.89	43.43	376,373
1996	1.79	0.75	1,328	365.89	47.17	485,901
1997	1.80	1.01	1,631	392.19	46.48	639,664
1998	0.22	-0.63	1,607	833.36	56.13	1,339,213
1999	1.14	0.33	1,276	911.37	80.69	1,162,910
2000	-1.24	-0.66	1,062	1280.32	87.92	1,359,695
2001	1.10	0.34	743	858.79	76.17	638,084
2002	0.63	0.29	703	260.50	57.46	183,133
2003	1.08	0.52	650	468.27	66.97	304,377
2004	1.10	0.49	761	600.22	66.88	456,765
2005	1.07	0.24	760	675.88	75.53	513,669
2006	0.66	0.33	759	756.03	75.69	573,826
2007	1.20	0.14	721	557.15	72.69	401,703
2008	0.02	0.00	527	752.70	71.24	396,674
2009	1.44	0.40	341	999.19	83.84	340,724
2010	0.50	0.13	453	614.32	124.78	278,285
2011	0.89	0.64	471	738.60	103.76	347,880
2012	1.37	0.72	480	473.17	82.00	227,120
2013	1.97	1.26	426	539.48	108.47	229,820
2014	1.90	0.83	540	1112.09	116.81	600,530
2015	1.85	1.27	461	1371.38	146.22	632,207
2016	1.36	0.97	388	1171.19	161.90	454,420
2017	1.17	0.95	360	916.61	157.58	329,978
1981-1989	0.25	-0.33	2,837	478.65	93.79	1,357,934
1990-2017	1.06	0.44	20,716	631.82	64.78	13,088,743

Table 3: Estimation of the time trend in acquirer announcement returns using year dummies

The table presents the results of regression analysis of acquirer announcement returns and related variables for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is Acquirer CAR % $[-3, +3]$, which is the cumulative abnormal return of the acquirer in the 7-day event window centered on the announcement date. The main explanatory variables in all columns are year dummies for each year during the period 1990–2017 (coefficients suppressed and shown graphically in Fig 1). Column(1) includes no control variables. Column (2) adds controls for acquirer- and deal-specific characteristics. Column (3) further adds acquirer industry (2-digit SIC level) fixed effects. Column (4) replaces acquirer industry fixed effects with bidder firm fixed effects. t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	No controls (1)	Controls (2)	Controls + ind. FE (3)	Controls + acq. FE (4)
Public target X stock		-3.66***	-3.49***	-3.30***
		(-10.18)	(-8.57)	(-5.99)
Public target X cash		-1.21***	-1.19***	-0.98***
		(-3.67)	(-3.69)	(-2.88)
Private target X cash		-1.25***	-1.24***	-0.93***
		(-4.64)	(-4.66)	(-3.06)
Private target X stock		-0.90***	-0.81***	-0.32
		(-3.03)	(-2.79)	(-1.19)
Subsidiary target X cash		-0.63**	-0.71**	-0.43
		(-2.27)	(-2.46)	(-1.58)
Same industry		-0.02	0.13	0.37*
		(-0.12)	(0.70)	(1.75)
Cross-border		-0.24	-0.30	-0.25
		(-1.10)	(-1.44)	(-1.00)
Hostile		-0.42	-0.47	-0.66
		(-0.99)	(-1.15)	(-1.21)
Tender offer		0.46	0.35	0.20
		(1.29)	(0.98)	(0.55)
Ln (Acquirer size)		-0.57***	-0.59***	-1.78***
		(-7.06)	(-7.40)	(-7.11)
Acquirer run-up		-1.69***	-1.68***	-1.71***
		(-5.18)	(-5.04)	(-4.38)
Acquirer idiosyncratic vol.		7.19	6.14	-12.18
		(0.58)	(0.53)	(-0.85)
Acquirer Tobin's Q		-0.02	-0.01	0.03
		(-0.45)	(-0.38)	(0.85)
Acquirer leverage		1.37**	1.22***	1.30
		(2.70)	(2.81)	(1.47)
Acquirer cash holdings		-0.17	-0.07	1.07
		(-0.27)	(-0.12)	(1.21)
Year FEs included	**SEE FIGURE 1**	**SEE FIGURE 1**	**SEE FIGURE 1**	**SEE FIGURE 1**
N (without singletons)	23,553	23,553	23,553	23,553

Table 4: Estimation of the time trend in acquirer announcement returns using a linear trend structure

The table presents the results of regression analysis of acquirer announcement returns for a sample of U.S. acquirers over the 1981-2017 period. In Panel A, the dependent variable in all columns is Acquirer CAR % [−3, +3], which is the cumulative abnormal return on the acquiring firm stock in the 7-day event window centered on the announcement date. In Panel B, the dependent variable is the estimated bidder fixed effect ($\widehat{BidderFE_i}$), as estimated in column (4) of Table 3. The main explanatory variable in all columns is a linear trend variable, *Year trend*, that takes the value of zero for the period 1981-1989 and increments by one every subsequent year. Column(1) includes no control variables. Column (2) adds controls for acquirer- and deal-specific characteristics. Column (3) further adds acquirer industry fixed effects (2-digit SIC level). Column (4) replaces acquirer industry fixed effects with bidder firm fixed effects (not applicable for Panel B). t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	No controls (1)	Controls (2)	Controls + ind. FE (3)	Controls + acq. FE (4)
Panel A: common component				
Year trend	**0.02** **(1.17)**	**0.06***** **(5.67)**	**0.06***** **(5.30)**	**0.17***** **(5.50)**
N (without singletons)	23,553	23,553	23,553	23,553
Panel B: firm-specific component				
Year trend	**-0.04**** **(2.64)**	**-0.12***** **(11.92)**	**-0.12***** **(11.44)**	**N/A** **N/A**
N (without singletons)	23,553	23,553	23,553	N/A

Table 5: Empirical proxies for bidder uniqueness

The table presents descriptive statistics (Panel A) and pairwise correlations (Panel B) of four empirical proxies for bidder uniqueness. *Uniqueness (ρ returns)* is defined as one minus the average correlation of daily stock return residuals of the bidder and its three closest peers from the same 2-digit SIC industry that are at least as large as the minimum of deal value and bidder size. Residuals are obtained from a two-factor model (market and 2-digit SIC industry portfolio) factors estimated over a one year prior to deal announcement subject to a minimum of one hundred non-missing observations. *Uniqueness (ρ sales)* is defined as one minus the average quarterly sales growth correlation of the bidder and its three closest peers from the same 2-digit SIC industry that are at least as large as the minimum of deal value and bidder size. Correlations are estimated over a five-year period prior to deal announcement subject to a minimum of eight non-missing observations. *Uniqueness (ρ ROA)* is defined as one minus the average correlation of quarterly ROAs of the bidder and its three closest peers from the same 2-digit SIC industry that are at least as large as the minimum of deal value and bidder size. Correlations are estimated over a five-year period prior to deal announcement subject to a minimum of eight non-missing observations. All correlation-based proxies are set to one when the average correlation between the bidder and its three closest peers is negative. *Uniqueness (HP)* is defined as one minus the average Hoberg and Phillips (2010, 2016) product similarity score between the bidder and its three closest peers from the 2-digit SIC industry that are at least as large as the minimum of deal value and bidder size, as of the year prior to deal announcement.

	N	**Mean**	**Median**	**St. Dev.**
Panel A: descriptive statistics				
Uniqueness (ρ ret)	22,917	0.801	0.808	0.091
Uniqueness (ρ sales)	18,978	0.330	0.302	0.193
Uniqueness (ρ ROA)	16,493	0.303	0.263	0.192
Uniqueness (HP)	14,747	0.806	0.822	0.094

	Uniqueness (ρ ret)	Uniqueness (ρ sales)	Uniqueness (ρ ROA)	Uniqueness (HP)
Panel B: pairwise correlations				
Uniqueness (ρ ret)	1			
Uniqueness (ρ sales)	0.286	1		
Uniqueness (ρ ROA)	0.340	0.600	1	
Uniqueness (HP)	0.276	0.250	0.257	1

Table 6: Bidder uniqueness and the cross-section of acquirer returns

The table presents the results of regression analysis of acquirer announcement returns for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is Acquirer CAR % [3, +3], which is the cumulative abnormal return on the acquiring firm stock in the 7-day event window centered on the announcement date. The main explanatory variables are proxies for bidder uniqueness based on stock return correlation *(Uniqueness (ρ returns))*, sales growth correlation *(Uniqueness (ρ sales))*, cash flow correlation *(Uniqueness (ρ ROA))* and product similarity *(Uniqueness (HP))*. All regressions include year fixed effects. Bidder- and deal-specific control variables as in Table 3, as well as acquirer industry (2-digit SIC) fixed effects are further included as indicated. t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Uniqueness (ρ ret)	**4.14*** **	**3.81*** **	**3.10** **									
	(3.72)	**(4.15)**	**(2.67)**									
Uniqueness (ρ sales)				**1.29*** **	**2.18*** **	**2.06*** **						
				(3.04)	**(8.95)**	**(5.71)**						
Uniqueness (ρ ROA)							**0.88* **	**1.87*** **	**1.43*** **			
							(1.90)	**(5.38)**	**(3.64)**			
Uniqueness (HP)										**6.17*** **	**4.11*** **	**4.77*** **
										(8.48)	**(7.45)**	**(6.32)**
Year FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Industry FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
N (without singletons)	22,917	22,917	22,917	18,978	18,978	18,977	16,493	16,493	16,492	14,747	14,747	14,746

Table 7: Bidder uniqueness and the composition effect: controlling for bidder fixed effects

The table presents the results of regression analysis of acquirer announcement returns for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is Acquirer CAR % [3, +3], which is the cumulative abnormal return on the acquiring firm stock in the 7-day event window centered on the announcement date. The main explanatory variables are proxies for bidder uniqueness based on stock return correlation *(Uniqueness (ρ returns))*, sales growth correlation *(Uniqueness (ρ sales))*, cash flow correlation *(Uniqueness (ρ ROA))* and product similarity *(Uniqueness (HP))*. All regressions include year fixed effects. Bidder- and deal-specific control variables as in Table 3, as well as acquirer industry (2-digit SIC) fixed effects are further included as indicated. t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uniqueness (ρ ret)	**2.99****	**2.51**						
	(2.62)	**(1.27)**						
Uniqueness (ρ sales)			**2.07*****	**0.75**				
			(5.98)	**(1.58)**				
Uniqueness (ρ ROA)					**1.47*****	**0.71**		
					(3.54)	**(1.10)**		
Uniqueness (HP)							**4.03*****	**0.67**
							(5.74)	**(0.27)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES	YES	YES
Industry FEs	YES	NO	YES	NO	YES	NO	YES	NO
Acquirer FEs	NO	YES	NO	YES	NO	YES	NO	YES
N (without singletons)	22,796	22,796	18,651	18,651	15,958	15,958	14,110	14,110

Table 8: Bidder uniqueness and the composition effect: direct association

The table presents the results of regression tests of the association between acquirer fixed effect estimates and proxies for bidder uniqueness for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is the estimated acquirer fixed effect from the regression model in column (4) of Table 3. The main explanatory variables are proxies for bidder uniqueness based on stock return correlation *(Uniqueness (ρ returns))*, sales growth correlation *(Uniqueness (ρ sales))*, cash flow correlation *(Uniqueness (ρ ROA))* and product similarity *(Uniqueness (HP))*. Bidder and deal-specific characteristics as in Table 3, as well as acquirer industry (2-digit SIC) fixed effects are included as indicated. t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Uniqueness (ρ ret)	**5.78*** **	**5.95*** **	**5.22*** **									
	(4.95)	**(5.89)**	**(4.60)**									
Uniqueness (ρ sales)				**5.04*** **	**3.04*** **	**2.71*** **						
				(10.15)	**(7.79)**	**(6.94)**						
Uniqueness (ρ ROA)							**4.79*** **	**2.62*** **	**2.29*** **			
							(9.25)	**(6.58)**	**(7.58)**			
Uniqueness (HP)										**3.79** **	**4.09*** **	**3.25*** **
										(2.36)	**(5.54)**	**(3.03)**
Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Industry FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
N (without singletons)	22,917	22,917	22,917	22,796	22,796	18,978	16,493	16,493	16,492	14,747	14,747	14,746

Table 9: Bidder uniqueness in the time-series

The table presents the results of regression analysis of empirical proxies for bidder uniqueness for a sample of U.S. acquirers over the 1981-2017 period (except for column (4) where the sample period is 1996-2017). The dependent variable in column (1) is a proxy for bidder uniqueness based on stock return correlation *(Uniqueness (ρ returns))*. The dependent variable in column (2) is a proxy for bidder uniqueness based on sales growth correlation *(Uniqueness (ρ sales))*. The dependent variable in column (3) is a proxy for bidder uniqueness based on cash flow correlation *(Uniqueness (ρ ROA))*. The dependent variable in column (4) is bidder uniqueness based on product similarity *(Uniqueness (HP))*. The main explanatory variable is a linear trend variable *(Year trend)* that takes the value of zero for the period 1981-1989 and increments by one every subsequent year. The coefficient shown in the table is scaled up by 100. All regressions include bidder- and deal-specific control variables as in Table 3, as well as acquirer industry (2-digit SIC) fixed effects. t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Uniqueness (ρ ret) (1)	Uniqueness (ρ sales) (2)	Uniqueness (ρ ROA) (3)	Uniqueness (HP) (4)
Year trend	**-0.36***** **(-4.49)**	**-0.13*** **(-1.91)**	**-0.22***** **(-3.22)**	**0.06** **(1.32)**
Controls	YES	YES	YES	YES
Industry FEs	YES	YES	YES	YES
N (without singletons)	22,917	18,977	16,492	14,746

Table 10: The evolution of total synergy gains and target returns

The table presents the results of regression analysis of various merger-related outcomes for a sample of U.S. acquirers and public U.S. targets over the period 1981-2017. Regressions in Panel A employ proxies for total synergy gains as the dependent variable. The dependent variable in column (1) is the *Combined CAR % [−3, +3]*, which is the announcement period abnormal returns of the bidder-target portfolio with market capitalizations as weights. The dependent variable in column (2) is Δ *OI/Assets [−1, +3]*, which is the industry (2-digit SIC) adjusted change in the combined firm operating income scaled by total assets from one year prior to 3 years following deal completion. The dependent variable in column (2) is Δ *OI/Sales [−1, +3]*, which is the industry (2-digit SIC) adjusted change in the combined firm operating income scaled by sales from one year prior to 3 years following deal completion. The dependent variable in column (4) is Δ *OI/Emp. [−1, +3]*, which is the industry (2-digit SIC) adjusted change in the combined firm operating income scaled by total employment from one year prior to 3 years following deal completion. Regressions in Panel B employ proxies for target firm gains as the dependent variable. The dependent variable in columns (1) and (2) is the *Target CAR % [−3, +3]*, which is the announcement period abnormal return of the target firm in the 7 day event window around the announcement. The dependent variable in column (3) is the *Target CAR % [−42, +3]*, which is the announcement period abnormal return of the target firm over the period from two months leading up to deal announcement to 3 days following the announcement. The dependent variable in column (4) is the *Target CAR % [Ann −42, Comp +3]*, which is the announcement period abnormal return of the target firm over the period of two months leading up to deal announcement to 3 days following deal completion (estimation is limited to completed deals only). The main explanatory variable in all columns is a linear trend variable, *(Year trend)*, that takes the value of zero for the period 1981-1989 and increments by one every subsequent year. All regressions include acquirer- and deal-specific controls, year fixed effects, and acquirer industry (2-digit SIC level) firm fixed effects. Regression in columns (1), (2), and (3) of Panel B further include controls for target characteristics mirroring those of the bidder. t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A	Combined CAR [−3, +3] (1)	Δ OI/Assets [−1, +3] (2)	Δ OI/Sales [−1, +3] (3)	Δ OI/Emp. [−1, +3] (4)
Year trend	**0.10***** **(4.31)**	**0.06**** **(2.06)**	**0.08**** **(2.16)**	**1.03**** **(2.33)**
Controls	YES	YES	YES	YES
Industry FEs	YES	YES	YES	YES
N (without singletons)	3,355	2,625	2,593	2,280

Panel B	Target CAR [−3, +3] (1)	Target CAR [−3, +3] (2)	Target CAR [−42, +3] (3)	Target CAR [−42, Comp +3] (4)
Year trend	**0.20*** **(1.83)**	**0.34***** **(2.97)**	**0.22*** **(1.90)**	**0.27*** **(1.73)**
Controls	YES	YES	YES	YES
Industry FEs	YES	YES	YES	YES
Target firm controls	NO	YES	YES	YES
N (without singletons)	3,356	3,096	3,096	2,311

Internet Appendix for

“Bidder-Specific Synergies and the Evolution of Acquirer Returns”

A Learning by doing and observing

A.1 Learning-by-doing: direct deal experience

In Internet Appendix Table 6 we address the possibility that the upward trending common component reflects a deal experience effect. We do sy by augmenting our baseline year trend specification (with acquirer fixed effects) with various measures of deal experience. For expositional clarity, and since the sample sizes change depending on the variable included, the table also repeats the baseline time trend estimation in Column (1). In Column (2) we control for the natural logarithm of deal experience, *Ln (Deal exper.)*, defined as the number of deals conducted by the acquirer since the beginning of our sample in 1981. *Ln (Deal exper.)* receives a negative and statistically insignificant coefficient, and inclusion of this variable increases the coefficient estimate on *Year trend* to 19 bps per year.

Because we do not observe deals conducted by our acquirers prior to the start of the sample, the deal experience variable *Ln (Deal exper.)* may be truncated. To address the issue of truncation, we use the first 5 years of our sample to define a new deal experience variable that counts only the deals conducted in the last 5 years, *Ln (Deal exper. 5 yr)*, and start the estimation in 1986. As before, we re-estimate the baseline year trend effect on the same sample (Column 3), which remains 17 bps per year. In Column (4), we add *Ln (Deal exper. 5 yr)*. The experience variable again receives a negative coefficient estimate of -0.40, which is now statistically significant. That is, the number of deals conducted by the acquirer in the prior 5 years is negatively associated with returns to its current deal. However, the time trend coefficient is unaffected.

Finally, in the last column of Internet Appendix Table 6, we replace *Ln (Deal exper. 5 yr)* with several indicator variables counting the number of deals conducted in the prior 5 years. The coefficient on the year trend variable is still 17 bps. The effect of acquisitiveness on acquirer returns is again negative, but it is statistically significant only for acquirers conducting up to 10 deals. Acquirers conducting more than 10 deals in the prior 5-year period experience returns that are indistinguishable from those who have no deal experience in the prior 5 years. Overall, Internet Appendix Table 6 provides little empirical support for attributing the upward trend in acquirer returns to learning-by-doing.

A.2 Learning-by-observing: age and maturity effects

In addition to learning-by-doing, which we measure above using actual deal experience, firms may also be "learning-by-observing". The latter effect is more generally a function of acquirer age and asset composition. For example, a firm is likely to learn over time from the acquisition experience of its industry rivals, and positive takeover gains may be more readily available in the presence of mature assets that are ripe for consolidation. These effects suggest a positive relationship between firm age and acquirer returns. It also suggests that late entrants into our sample of acquisitions may be less skilled than earlier entrants. The latter is generally consistent with our finding that failure to control for changing sample composition brings down the unconditional average takeover gain.

Internet Appendix Table 7 presents the results of our analysis of age and maturity effects. We measure bidder age using two variables, *Acquirer age (CRSP)* and *Acquirer age (foundation)*. The former is the number of years that the acquirer has been covered by CRSP, while the latter is the number of years since the firm was founded. Data on the year of foundation, which are maintained by Jay Ritter and Laura Field (Field and Karpoff, 2002; Loughran and Ritter, 2004), are downloaded from Jay Ritter's website. When the foundation date in the Field-Ritter dataset is unavailable, we use the foundation year provided by Capital IQ. When the latter is also unavailable, we use the first year the firm appears on CRSP.

Since the year trend variable is collinear with age in a firm fixed effects specification, Panel A of Internet Appendix Table 7 drops the firm fixed effects from the regression analysis. Acquirer fixed effects are, however, brought back in Panel B where the two age variables are replaced by two proxies for acquirer maturity: *Acquirer RE/TE* and *Acquirer life Cycle*. *Acquirer RE/TE* follows DeAngelo, DeAngelo, and Stulz (2006) and uses the ratio of retained earnings to total equity (a measure of the mix of earned and contributed capital) as a proxy for firm maturity. *Acquirer life Cycle* is an ordinal variable (with values between 1 and 5) developed by Dickinson (2011) based on the signs of cash flows from operating, financing, and investing activities. Higher values of *Acquirer life Cycle* indicates later (more mature) life cycle stages. As *Acquirer life Cycle* requires Compustat cash-flow-statement information, it is available from year 1988 onwards.

In the first two columns in Panel A of Internet Appendix Table 7, we re-estimate the coefficient on the year trend variable after replacing acquiring firm fixed effects with acquirer cohort (year of birth) fixed effects. If the time trend we document in a firm fixed effects specification is related to the age of the firm, we should be able to uncover the same temporal trend in acquirer returns when using cohort fixed effects instead. Columns (1) and (2) in Panel A show that this is not the case: in both columns, the coefficient estimate on the year trend variable is only 6-7 bps—similar to the 6 bps in our baseline specification with industry fixed effects in Table 4 in our main analysis. Thus, it appears that the time trend in acquirer gains is unrelated to acquirer age. In columns (3) and (4) of Panel A we directly test whether (the log of) acquirer age has any explanatory power for the cross-section of acquirer returns in the usual acquirer CAR specification with control variables and industry fixed effects. In both cases the coefficients on the age variables are indistinguishable from zero.

Panel B of Appendix Table 7 further confirms that the temporal trend in acquirer gains that we uncover in a firm fixed effects specification is unrelated to maturity effects. The year trend coefficient estimate remains at 0.16 bps throughout the columns. Neither *Acquirer RE/TE* in Column (2) nor *Acquirer life cycle* in Column (4) has explanatory power.

B Trends in corporate governance

The extant literature points to a potential for better corporate governance to improve acquisition decisions. For example, Datta, Iskandar-Datta, and Raman (2001) show that acquirers whose managers have a higher fraction of equity-based compensations make better acquisitions, while Masulis, Wand, and Xie (2007) report that acquirers with more antitakeover defences, such as staggered boards, tend to make worse acquisition decisions.

There has been a trend towards improved governance over our sample period, including a decline in the frequency of staggered boards (Cremers, Litov, and Sepe, 2017), an increase in board independence (Duchin, Matsusaka, and Ozbas, 2010), and increased equity-based compensation (Edmans, Gabaix, and Jenter, 2017). Shareholder oversight may also have improved with the rise of institutional ownership (Lewellen, 2011) in general, and by increased investor activism in particular (Brav, Jiang, Ma, and Tian, 2018). Below, we examine whether the time trend in acquirer returns is associated with these types of governance improvements.

In Internet Appendix Table 8, we augment our baseline year trend specification (with bidder fixed effects) with various proxies for corporate governance quality, once again re-estimating the baseline model on the same sample for comparability. We use four governance proxies that exhibit a trend over time, namely, institutional blockholder ownership, board independence, the presence of a staggered board, and CEO equity-based compensation. The table starts with institutional blockholder ownership, *Acquirer inst. block. own*, in Column (2) since this variable is available for almost the entire acquisition sample. The source of Institutional blockholder ownership is Thomson Reuters 13F holdings. Surprisingly, *Acquirer inst. block. own* receives a significantly *negative* coefficient in our firm fixed effects specification. Moreover, inclusion of this variable raises the time trend coefficient estimate in Column (1) slightly, from 17bps to 18bps. Thus, we conclude that the temporal trend in acquirer gains is not related to the temporal increase in institutional ownership.

In columns (4) through (6) of Internet Appendix Table 8, we explore the role of board independence and staggered boards. Board independence is the fraction of outside directors on the board. The sources of board information are Boardex (which covers a large cross-section of firms but starts only in the year 2000) and Institutional Investor Services (ISS, which provides directors data for larger firms back to 1997). Each firm is restricted to a single board data source. Given our firm fixed effects specification, this restriction ensures that there are no structural breaks in board independence within firm.

The baseline year-trend estimate for the subsample of firms with board independence in Column (3) is 15 bps. We then add *Acquirer % outside dir.* as well as its interaction with an indicator for public targets, since Dahya, Golubov, Petmezas, and Travlos (2019) show that the effect of outside directors on the board is most pronounced in public firm acquisitions. As expected, the interaction term receives a positive and significant coefficient, suggesting that board independence is associated with higher acquirer returns when the target is public. At the same time, the year-trend coefficient is unchanged. We conclude that increased board independence cannot explain the temporal increase in merger gains.

Turning to Column (6), we collect information on staggered boards from ISS and from the (hand-collected) staggered board data for newly public firms in Johnson, Karpoff, and Yi (2018).[1] Column (5) establishes that the baseline year-trend estimate for the subsample of firms with data on staggered boards is 13 bps per year. Adding the indicator variable *Acquirer staggered board* for staggered boards in Column (6) does not change our inferences as the coefficient on this variable is statistically insignificant. The time trend in acquirer returns is reduced slightly from 13 bps to 11 bps.

Finally, in Column (8) of Internet Appendix Table 8, we explore whether an increase over time in the fraction of CEO equity-based compensation is associated with the positive time trend in acquirer

[1]We thank the authors for sharing this variable with us.

returns. Our data sources are Execucomp (which covers large firms only) Capital IQ People Intelligence. People Intelligence provides only limited information on the value of option awards and stock grants. Thus, whether the data source is Execucomp or People Intelligence, our proxy variable for the fraction of equity-based compensation, *Acquirer CEO EBC*, is total compensation minus salary and cash bonus, divided by total compensation. Once again, to avoid structural breaks in proxy variable, we restrict each firm to a single compensation-data source.

Notice first that the time trend estimate for the subsample with compensation data in Column (7) is 9 bps per year and significant at the 5% level. In Column (8), *Acquirer CEO EBC* receives an insignificant coefficient, and the time trend coefficient remains at 9 bps. The main takeaways is that the the addition of CEO equity-based compensation as a control does not change the magnitude of the effect.

C Trends in industry concentration

Gutiérrez and Philippon (2017) and Grullon, Larkin, and Michaely (2019) show that U.S. industries have become more concentrated over time, prompting us to consider market power effects (either upstream or downstream) as a potential source of increased merger gains. Note, however, that the evidence reported in Internet Appendix Table 4 is inconsistent with market power scenarios since the temporal increase in the common component of bidder gains is just as present in cross-industry and cross-border transactions as in horizontal mergers and deals between domestic firms. More generally, the merger literature going back to Eckbo (1983, 1985) and Eckbo and Wier (1985) rejects the predictions of the market power hypothesis for merger-induced CARs to the industry rivals, upstream suppliers and downstream consumers of merging firms.[2]

Nevertheless, it is possible that the effects of mergers on rivals, suppliers, and customers have changed over time, especially in light of rising industry concentration. To investigate this possibility, we compute CARs for portfolios of corporate rivals, customers, and suppliers of the merging firms for deals in our sample and regress them on the *Year trend* variable.[3] Since monopolistic and monopsonistic power

[2] Eckbo (1992), Fee and Thomas (2004), Shahrur (2005), Aktas, de Bodt, and Roll (2007), Bhattacharyya and Nain (2011), and Becher, Mulherin, and Walkling (2012).

[3] Following Fee and Thomas (2004), we define corporate customers (suppliers) as all firms reported as major clients (suppliers) by either the bidder or the target in compliance with SFAS 131 disclosure obligations. These customer-supplier links are widely used in research on supply chain effects; we use the dataset from Barrot and Sauvagnat (2016) made available by the authors. Following Fee and Thomas (2004) and Shahrur (2005), we define corporate rivals as all firms in the same 4-digit SIC industry as the bidder, which is also the industry of the target in horizontal deals.

hypotheses are largely specific to horizontal mergers, we interact the time trend variable with an indicator for horizontal (same 4-digit SIC) deals. If the temporal increase in bidder gains is related to market power effects, we would expect rival firm wealth effects to improve over time[4], customer and supplier wealth effects to deteriorate over time, and any such effects to be more pronounced for horizontal deals. Results reported in Internet Appendix Table 9 reject these predictions: there is no evidence to suggest that rivals are progressively better off or that customers and suppliers are progressively worse off over the sample period, with the exception of rival effects when the rival firm portfolio is value weighted. Horizontal deals exhibit no incremental effects. Overall, the results are inconsistent with market power/buyer power effects as a driver of the conditional increase in bidder gains.

The trend toward higher industry concentration is of further interest because the degree of product market competition may constrain corporate mismanagement (Giroud and Mueller, 2010, 2011). Since firms in highly competitive industries operate with thin profit margins, there is more room for mismanagement of free cash flow in monopolistic industries where profits are abundant. Mismanagement of target firms may provide profit-opportunities for bidders (Manne, 1965; Scharfstein, 1988; Kini, Kracaw, and Mian, 2004), while mismanagement of bidders lowers expected acquirer returns (Jensen, 1986; Masulis, Wand, and Xie, 2007). Therefore, we test whether time-series variation in industry concentration helps explain the common component of acquirer returns.

In Internet Appendix Table 10, we augment our baseline regression specification for the year-trend variable (full set of controls, firm fixed effects) with 2-digit SIC industry variables such as the sales-based Herfindahl-Hirschman index (HHI), the number of firms in the industry, and industry profit margins (using a 3-digit SIC industry definition yields similar inferences). The variables are introduced one at a time to avoid multi-collinearity. In Column (2), we add the HHI of acquirer and target industries (*Target SIC2 HHI* and *Acquirer SIC2 HHI*). As shown, while target industry concentration help explain some of the cross-sectional variation in bidder gains, but it does not reduce the baseline 17 bps estimate of the year trend from Column (1). The magnitude is actually increased to 18 bps.

In column (3) we replace HHI with the (log) number of firms in an industry (*Target SIC2 Ln (# of firms)* and *Acquirer SIC2 Ln (# of firms)*). The results are consistent with the disciplinary effects of industry concentration, whereby acquirers from industries with more firms exhibit higher returns. How-

[4]Note that positive effects on rivals are also consistent with information revelation about the availability of gains from merger or the probability of such mergers.

ever, the inclusion of these explanatory variables causes the year-trend coefficient estimate to *increase* to 22 basis points per year. Finally, in column (4) we use industry profit margins as a proxy for competitiveness (*Target SIC2 EBIT/Sales* and *Acquirer SIC2 EBIT/Sales*).[5] Once again, we find that the coefficient on the year trend variable is unaffected relative to the baseline specification in Column (1). The coefficients estimates for the industry profit margin variables are both statistically insignificant. In sum, the temporal increase in the common component of acquirer returns is unrelated to the recent trend toward increased industry concentration.

D Trends in the market for M&A advisory

Bao and Edmans (2011) document that M&A advisors are significantly differentiated in terms of the quality of their M&A advice—producing significant advisor-specific components (advisor fixed effects) in acquirer returns. Sibilkov and McConnell (2014) further show that, not only are investment banks characterized by persistent client performance, but bidders appear to seek out this information when selecting future advisors. That is, advisors whose clients exhibit higher takeover gains attract more advisory mandates going forward. We therefore examine whether the temporal increase in bidder gains (the common year-trend) documented in this paper is related to advisor heterogeneity—as more qualified advisors capture a greater share of the advisory market over time.

We collect information on investment banks that advised our sample bidders. Since SDC does not report advisor codes consistently (e.g., Lazard can be referred to as LAZ, LAZARD, LAZARD-BRO, LAZARD-HOUSES, etc.), we manually go over all unique advisor codes and collapse them to a much coarser set of advisor IDs. We do so by cross-checking advisor codes against the full advisor name reported by SDC, coupled with extensive internet searches in order to take into account name changes. Through this process, we also account for mergers and acquisitions between financial advisors.[6] Initially, advisor information is available for 9,757 deals advised by 739 unique advisors (an additional 360 deals are flagged as "in-house" deals where no advisor was retained). After collapsing advisor IDs and eliminating singleton

[5]We obtain similar results when we use revenue divided by cost of goods sold as a proxy for industry markups, as per De Loecker, Eeckhout, and Unger (2018).

[6]The latter requires certain judgement to be exercised. Our guiding principle is to retain the same advisor ID when the reorganization is unlikely to have led to major changes to the investment banking operations (e.g. a simple transfer of control), and to assign a new advisor ID when the converse is true. For example, when a commercial bank without significant investment banking operations acquires an investment bank, we retain the same advisor ID. In contrast, when two major financial advisors merge (e.g. Bank of America and Merrill Lynch in 2008), we assign a new advisor ID to the merged entity. A complete record of this process is available from the authors upon request.

advisors (as well as singleton bidders in this reduced sample) we are left with 6,179 deals advised by 238 unique advisors.

Internet Appendix Table 11 shows the result of augmenting our acquirer return regression with advisor fixed effects in order to control for the possibility that the composition of advisors is changing over time. As before, we begin in Column (1) with a baseline regressions for the subsample of firms with advisor data. It shows a baseline year trend effect of 13 bps in the sample of 6,179 deals, significant at the 1% level. Adding advisor fixed effects (238 unique advisor dummies) in Column (2), the time trend coefficient drops to 11 bps and statistical significance drops to a 10% level. This is consistent with the hypothesis that the rising trend in bidder gains is related to advisor composition. That is, higher bidder gains over time are to some extent explained by advisor heterogeneity: bidders are gravitating towards higher fixed effect advisors over time. Equivalently, higher fixed effect advisors are gaining market share over time and/or high fixed effect advisors are entering the market in the later parts of our sample.

Is the reduction of the coefficient on the year trend from 13 bps in Column (1) to 11 bps in Column (2) statistically significant? One way to assess this question is to control for "random" advisor fixed effect. We perform 1,000 permutation tests whereby we randomly assign advisor IDs across deals and rerun the advisor fixed effects specification. Internet Appendix Figure 1 reports the distribution of resulting year trend coefficients. Only one of the 1,000 permutations results in a year trend coefficient below 11 basis points, and the distribution is centered around 13 basis points, which is the value of the year trend coefficient in our baseline specification without advisor fixed effects altogether. This suggests that the reduction in the coefficient on the year trend variable we observe in the real data is not a statistical artifact. Rather, a consistent explanation is that competitive forces in the market for merger advisory services have shifted mandates towards more qualified advisors, resulting in improved bidder performance over time.

Notwithstanding the results in Column (2), the notion that bidders are gravitating toward better advisors over time is at best a partial explanation for the positive time trend in acquirer returns. The reason is that, in Column (3), which uses the part of our total sample for which we do not have advisor identities, we continue to observe a significantly positive year trend effect of 15 bps per year. A significant portion of the acquisitions in Column (3) are likely "in-house" deals, in which the acquirer is not advised by an investment bank.

References (Internet Appendix)

Aktas, Nihat, Eric de Bodt, and Richard Roll, 2007, Is European M&A regulation protectionist?, *Economic Journal* 117, 1096–1121.

Bao, Jack, and Alex Edmans, 2011, Do investment banks matter for M&A returns?, *Review of Financial Studies* 24, 2286–2315.

Barrot, Jean-Noël, and Julien Sauvagnat, 2016, Input specificity and the propagation of idiosyncratic shocks in production networks, *The Quarterly Journal of Economics* 131, 1543–1592.

Becher, David A., J. Harold Mulherin, and Ralph A. Walkling, 2012, Sources of gains in corporate megers: Refined tests from a neglected industry, *Journal of Financial and Quantitative Analysis* 47, 57–89.

Bhattacharyya, Sugato, and Amrita Nain, 2011, Horizontal acquisitions and buying power; A product market analysis, *Journal of Financial Economics* 99, 97–115.

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, 2018, How does hedge fund activism reshape corporate innovation?, *Journal of Financial Economics* 130, 237–264.

Cremers, Martijn K. J., Lubomir P. Litov, and Simone M. Sepe, 2017, Staggered boards and long-tern firm value, revisited, *Journal of Financial Economics* 126, 422–444.

Dahya, Jay, Andrey Golubov, Dimitris Petmezas, and Nickolaos G. Travlos, 2019, Governance mandates, outside directors, and acquirer performance, *Journal of Corporate Finance* 59, 218–238.

Datta, Sudip, Mai Iskandar-Datta, and Kartik Raman, 2001, Executive compensation and corporate acquisition decisions, *Journal of Finance* 56, 2299–2336.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger, 2018, The rise of market power and the macroeconomic implications, Working Paper, KU Leuven, UPF Barcelona, and Harvard University.

DeAngelo, Harry, Linda DeAngelo, and René M. Stulz, 2006, Dividend policy and the earned/contributed capital mix: A test of the life-cycle theory, *Journal of Financial Economics* 81, 227–254.

Dickinson, Victoria, 2011, Cash flow patterns as a proxy for firm life cycle, *Accounting Review* 86, 1964–1994.

Duchin, Ran, John G. Matsusaka, and Oguzhan Ozbas, 2010, When are outside directors effective?, *Journal of Financial Economics* 96, 195–214.

Eckbo, B. Espen, 1983, Horizontal mergers, collusion, and stockholder wealth, *Journal of Financial Economics* 11, 241–272.

——— , 1985, Mergers and the market concentration doctrine: Evidence from the capital market, *Journal of Business* 58, 325–349.

——— , 1992, Mergers and the value of antitrust deterrence, *Journal of Finance* 47, 1005–1029.

——— , and Peggy Wier, 1985, Antimerger policy under the Hart-Scott-Rodino Act: A reexamination of the market power hypothesis, *Journal of Law and Economics* 28, 119–149.

Edmans, Alex, Xavier Gabaix, and Dirk Jenter, 2017, Executive compensation: A survey of theory and evidence, in Benjamin E. Hermalin, and Michael S. Weisbach, ed.: *Handbook of the Economics of Corporate Governance*, vol. 1 . chap. 7, pp. 383–539 (Elsevier, Amsterdam).

Fee, C. E., and S. Thomas, 2004, Sources of gains in horizontal mergers: Evidence from customers, supplier, and rival firms, *Journal of Financial Economics* 74, 423–460.

Field, L. C., and J. M. Karpoff, 2002, Takeover defenses at IPO firms, *Journal of Finance* 57, 1857–1889.

Giroud, Xavier, and Holger M. Mueller, 2010, Does corporate governance matter in competitive industries?, *Journal of Financial Economics* 95, 312–331.

———, 2011, Corporate governance, product market competition, and equity prices, *Journal of Finance* 66, 563–600.

Grullon, Gustavo, Yelena Larkin, and Roni Michaely, 2019, Are US industries becoming more concentrated?, *Review of Finance* forthcoming.

Gutiérrez, Germán, and Thomas Philippon, 2017, Declining competition and investment in the US, Working Paper, New York University.

Hoberg, Gerard, and Gordon Phillips, 2010, Product market synergies and competition in mergers and acquisitions: A text-based analysis, *Review of Financial Studies* 23, 3773–3811.

———, 2016, Text-based network industries and endogenous product differentiation, *Journal of Political Economy* 124, 1423–1465.

Jensen, Michael C., 1986, Agency costs of free cash flow, corporate finance and takeovers, *American Economic Review* 76, 323–329.

Johnson, William, Jonathan M. Karpoff, and Sangho Yi, 2018, The lifecycle effects of firm takeover defenses, Working Paper, Suffolk University, University of Washington, and Sogang University.

Kini, Omesh, William Kracaw, and Shezad Mian, 2004, The nature and discipline by corporate takeovers, *Journal of Finance* 59, 1511–1552.

Lewellen, Jonathan, 2011, Institutional investors and the limits of arbitrage, *Journal of Financial Economics* 102, 62–80.

Loughran, Tim, and Jay R. Ritter, 2004, Why has IPO underpricing changed over time?, *Financial Management* 33, 5–37.

Manne, Henry G., 1965, Mergers and the market for corporate control, *Journal of Political Economy* 73, 110–120.

Masulis, Ronald W., Cong Wand, and Fei Xie, 2007, Corporate governance and acquirer returns, *Journal of Finance* 62, 1851–1889.

Officer, Micah S., 2003, Termination fees in mergers and acquisitions, *Journal of Financial Economics* 69, 431–467.

Scharfstein, David, 1988, The disciplinary role of takeovers, *The Review of Economic Studies* 55, 185–199.

Shahrur, H., 2005, Industry structure and horizontal takeovers: Analysis of wealth effects on rivals, suppliers, and corporate customers, *Journal of Financial Economics* 76, 61–98.

Sibilkov, Valeriy, and John J. McConnell, 2014, Prior client performance and the choice of investment bank advisors in corporate acquisitions, *Review of Financial Studies* 27, 2474–2503.

Internet Appendix Table 1: Variable definitions

Variable	Definition
Acquirer characteristics	
Acquirer CAR % [−3, +3]	Cumulative abnormal return on the acquiring firm stock in the event window [−3, +3] centered on the announcement day. Abnormal returns are computed using the market model with parameters estimated over the period starting 300 days and ending 46 days prior to the announcement. CRSP-value weighted index is used as the market return. For firms with multiple classes of common stock we use the weighted-average cumulative abnormal return on the different classes with market capitalizations of the respective classes as weights (from CRSP).
Acquirer size	Market capitalization of the acquiring firm 4 days prior to the announcement (in U.S. $ million), computed as the stock price times the number of shares outstanding (from CRSP).
Acquirer Tobins Q	Tobins Q of the acquiring firm computed as book value of assets minus book value of common equity (from Compustat) plus the market value equity (from CRSP) divided by the book value of assets (from Compustat).
Acquirer leverage	Leverage ratio of the acquiring firm computed as total debt divided by total assets (from Compustat).
Acquirer cash holdings	Cash holdings of the acquiring firm computed as cash and cash equivalents divided by total assets (from Compustat).
Acquirer idiosyncratic vol.	Idiosyncratic stock return volatility of the acquiring firm computed as the standard deviation of market model residuals. The market model is estimated over the period starting 300 days and ending 46 days prior to the announcement using CRSP value-weighted index as the market return (from CRSP).
Acquirer run-up	Buy-and-hold abnormal return on the acquiring form stock over the period starting 300 days and ending 46 days prior to the announcement. CRSP value-weighted index is the market return (from CRSP).
Acquirer age (CRSP)	Number of years the acquiring firm stock has been covered in CRSP, defined as the year of the acquisition minus the year the stock first appeared in CRSP.
Acquirer age (foundation)	Number of years since the firm was founded, defined as the year of the acquisition minus the foundation year. We use the foundation year from the Field-Ritter dataset in the first instance (from Jay Ritters website), the foundation year from Capital IQ when the latter is unavailable, and the year the firms stock first appeared in CRSP as the last resort.
Acquirer inst. block own.	Percentage of acquiring firms shares owned by institutional blockholders, defined as institutions holding at least 5% of the outstanding shares (from Thomson Reuters 13f holdings).
Acquirer % outside dir.	Percentage of outside directors on the acquiring firm board of directors (from Boardex and ISS).
Acquirer staggered board	Indicator variable taking the value of one when the acquiring firm has a staggered (classified) board and zero otherwise (from ISS and Johnson, Karpoff, and Yi (2018)).
Acquirer CEO EBC	Equity-based compensation of the acquiring firm CEO, defined as total compensation minus salary and bonus divided by total compensation (from Execucomp and People Intelligence).
Acquirer RE/TE	Mix of earned and contributed capital of the acquiring firm, defined as the ratio of retained earnings to total shareholders equity following DeAngelo, DeAngelo, and Stulz (2006) (from Compustat).
Acquirer life cycle	Life cycle stage of the acquiring firm based on the signs of cash flows from operating, financing, and investing activities following Dickinson (2011). This is an ordinal variable taking the values between 1 and 5, with higher values indicating later life cycle stages (from Compustat).
Deal exper.	Deal experience of the acquiring firm, defined as the number of deals conducted by the acquirer since the beginning of our sample in 1981 (from Thomson Reuters SDC).
Deal exper. (5-yr.)	5-year deal experience of the acquiring firm, defined as the number of deals conducted by the acquirer in the 5 years preceding the announcement (from Thomson Reuters SDC).

Internet Appendix Table 1: Variable definitions (continued)

Variable	Definition
Deal characteristics	
Deal value	Transaction value (in U.S. $ million) (from Thomson Reuters SDC).
Deal relative size	Relative size of the deal, defined as transaction value (from Thomson Reuters SDC) divided by acquiring firm market capitalization 4 days prior to the announcement (from CRSP).
Public target	Indicator variable taking the value of one when the target firm is a public firm and zero otherwise (from Thomson Reuters SDC).
Private target	Indicator variable taking the value of one when the target firm is a private firm and zero otherwise (from Thomson Reuters SDC).
Subsidiary target	Indicator variable taking the value of one when the target firm is a subsidiary firm and zero otherwise (from Thomson Reuters SDC).
Cash	Indicator variable taking the value of one when the consideration offered is 100% cash and zero otherwise (from Thomson Reuters SDC).
Stock	Indicator variable taking the value of one when consideration offered includes acquiring firm stock and zero otherwise (from Thomson Reuters SDC).
Same industry	Indicator variable taking the value of one when the acquiring and target firms share the same 2-digit SIC code and zero otherwise (from Thomson Reuters SDC).
Cross-border	Indicator variable taking the value of one when the target firm is foreign and zero otherwise (from Thomson Reuters SDC).
Hostile	Indicator variable taking the value of one when the transaction is flagged as hostile or unsolicited (from Thomson Reuters SDC).
Tender offer	Indicator variable taking the value of one when the transaction is flagged as a tender offer (from Thomson Reuters SDC).
Combined CAR % [−3, +3]	Cumulative abnormal return of the combined firm in the event window [−3, +3] centered on the announcement day, defined as the weighted-average of Acquirer CAR % [−3, +3] and Target CAR % [−3, +3] with market capitalizations 4 days prior to the announcement as weights (from CRSP).
Target CAR % [−3, +3]	Cumulative abnormal return on the target firm stock in the event window [−3, +3] centered on the announcement day. Abnormal returns are computed using the market model with parameters estimated over the period starting 300 days and ending 46 days prior to the announcement. CRSP-value weighted index is used as the market return. For firms with multiple classes of common stock we use the weighted-average cumulative abnormal return on the different classes with market capitalizations of the respective classes as weights (from CRSP).
Offer premium % (4 wk.)	Offer premium relative to the target stock price 4 weeks prior to the announcement (from Thomson Reuters SDC). Following Officer (2003), values below 0% and above 200% are set to missing.
Year trend	Counter variable taking the value of zero for deals announced during the years 1981-1989 and incrementing by one for each subsequent year. When the estimation sample starts later than 1981 due to the availability of another variable of interest, Year trend is redefined such that it takes the value of one for deals announced in the first five available years and increments by one in each subsequent year.
Industry characteristics	
Target SIC2 HHI	Sales-based Herfindahl-Hirschman index of the target firm industry based on 2-digit SIC code (from Compustat).
Acquirer SIC2 HHI	Sales-based Herfindahl-Hirschman index of the acquiring firm industry based on 2-digit SIC code (from Compustat).
Target SIC2 # of firms	Number of firms in the target firm industry based on 2-digit SIC code (from Compustat).
Acquirer SIC2 # of firms	Number of firms in the acquiring firm industry based on 2-digit SIC code (from Compustat).
Target SIC2 EBIT/Sales	Profit margins, defined as EBIT divided by sales, in the target firm industry based on 2-digit SIC code (from Compustat).
Acquirer SIC2 EBIT/Sales	Profit margins, defined as EBIT divided by sales, in the acquiring firm industry based on 2-digit SIC code (from Compustat).

Internet Appendix Table 1: Variable definitions (continued)

Variable	Definition
Bidder uniqueness proxies	
Uniqueness (ρ ret)	One minus the average correlation of daily stock return residuals of the bidder and its three closest peers from the same 2-digit SIC industry that are at least as large as the minimum of deal value and bidder size. Residuals are obtained from a two-factor model (market and 2-digit SIC industry portfolio) factors estimated over a one year prior to deal announcement subject to a minimum of one hundred non-missing observations. The value is set to one when the average correlation between the bidder and its three closest peers is negative. (from CRSP).
Uniqueness (ρ sales)	One minus the average quarterly sales growth correlation of the bidder and its three closest peers from the same 2-digit SIC industry that are at least as large as the minimum of deal value and bidder size. Correlations are estimated over a five-year period prior to deal announcement subject to a minimum of eight non-missing observations. The value is set to one when the average correlation between the bidder and its three closest peers is negative (from Compustat).
Uniqueness (ρ ROA)	One minus the average correlation of quarterly ROAs of the bidder and its three closest peers from the same 2-digit SIC industry that are at least as large as the minimum of deal value and bidder size. Correlations are estimated over a five-year period prior to deal announcement subject to a minimum of eight non-missing observations. The value is set to one when the average correlation between the bidder and its three closest peers is negative (from Compustat).
Uniqueness (HP)	One minus the average Hoberg and Phillips (2010, 2016) product similarity score between the bidder and its three closest peers from the 2-digit SIC industry that are at least as large as the minimum of deal value and bidder size, as of the year prior to deal announcement (from Hoberg-Phillips data library).
Proxies for combined firm efficiency gains	
Δ OI/Assets [−1, +3]	Industry-adjusted (2-digit SIC) change in the combined firm operating income scaled by total assets from one year prior to three years following deal completion. An aggregation of bidder and target figures is used as a proxy for the combined firm prior to the deal (from Compustat).
Δ OI/Sales [−1, +3]	Industry-adjusted (2-digit SIC) change in the combined firm operating income scaled by sales from one year prior to three years following deal completion. An aggregation of bidder and target figures is used as a proxy for the combined firm prior to the deal (from Compustat).
Δ OI/Emp. [−1, +3]	Industry-adjusted (2-digit SIC) change in the combined firm operating income scaled by the number of employees from one year prior to three years following deal completion. An aggregation of bidder and target figures is used as a proxy for the combined firm prior to the deal (from Compustat).
Proxies for rival, customer, and supplier firm wealth effects	
EW (VW) Rival CAR % [−3, +3]	Equal-weighted (value-weighted) average announcement period abnormal return of corporate rivals of the acquirer in the event window [−3, +3] centered on the announcement day. Rivals are defined as all firms in the same 4-digit SIC industry. The definition of acquirer rivals' abnormal returns follows that for Acquirer CAR % [−3, +3] (from CRSP).
EW (VW) Customer CAR % [−3, +3]	Equal-weighted (value-weighted) average announcement period abnormal return of corporate customers of the merging firms in the event window [−3, +3] centered on the announcement day. Customers are defined as all firms reported by the bidder and the target as part of their major client disclosure requirements. The definition of customers' abnormal returns follows that for Acquirer CAR % [−3, +3] (from CRSP).
EW (VW) Supplier CAR % [−3, +3]	Equal-weighted (value-weighted) average announcement period abnormal return of corporate suppliers of the merging firms in the event window [−3, +3] centered on the announcement day. Suppliers are defined as all firms selling to the bidder and the target, identified as part of their major client disclosure requirements. The definition of suppliers' abnormal returns follows that for Acquirer CAR % [−3, +3] (from CRSP).

Internet Appendix Table 2: M&A sample: descriptive statistics

The table presents descriptive statistics for a sample of U.S. M&A deals over the period 1981-2017. All bidders are U.S. public firms with common stock listed on NYSE, Nasdaq, or Amex with a market capitalization of at least $1 million and a stock price of at least $1. All targets are either U.S. or foreign public, private, and subsidiary firms. Deals with missing transaction values, deals worth less than U.S. $1 million or smaller than 1% of acquirer market capitalization, and deals falling within 5 days of a quarterly earnings announcement are excluded. All variables are defined in Internet Appendix Table 1.

	N	**Mean**	**St. Dev.**	**10 pctl.**	**25 pctl.**	**Median**	**75 pctl.**	**90 pctl.**
Deal value (U.S.$ mil.)	23,553	451.38	2,954.03	5.20	14.03	46.41	176.04	637.87
Deal relative size	23,553	0.24	0.45	0.02	0.04	0.09	0.24	0.62
Public target X stock	23,553	0.16	0.36	0	0	0	0	1
Public target X cash	23,553	0.07	0.25	0	0	0	0	0
Private target X cash	23,553	0.19	0.39	0	0	0	0	1
Private target X stock	23,553	0.28	0.45	0	0	0	1	1
Subsidiary target X cash	23,553	0.22	0.41	0	0	0	0	1
Subsidiary target X stock	23,553	0.10	0.30	0	0	0	0	0
Relative size	23,553	0.24	0.45	0.02	0.04	0.09	0.24	0.62
Same industry	23,553	0.62	0.49	0	0	1	1	1
Cross-border	23,553	0.13	0.33	0	0	0	0	1
Hostile	23,553	0.02	0.13	0	0	0	0	0
Tender offer	23,553	0.04	0.21	0	0	0	0	0
Acquirer CAR % $[-3, +3]$	23,553	0.97	8.97	-8.37	-3.46	0.33	4.69	11.17
Acquirer size (U.S.$ mil.)	23,553	3,531.14	15,016.58	50.29	146.24	523.37	1,826.25	6,181.61
Acquirer run-up	23,553	0.12	0.52	-0.33	-0.15	0.03	0.25	0.60
Acquirer idiosyncratic vol.	23,553	0.03	0.02	0.01	0.02	0.02	0.04	0.05
Acquirer Tobin's Q	23,553	2.61	6.08	1.02	1.13	1.57	2.43	4.17
Acquirer leverage	23,553	0.23	0.20	0.00	0.06	0.19	0.34	0.51
Acquirer cash holdings	23,553	0.16	0.19	0.01	0.03	0.08	0.22	0.44
Uniqueness (ρ ret)	22,917	0.80	0.09	0.70	0.76	0.81	0.85	0.90
Uniqueness (ρ sales)	18,978	0.33	0.19	0.11	0.19	0.30	0.43	0.58
Uniqueness (ρ ROA)	16,493	0.30	0.19	0.10	0.17	0.26	0.39	0.55
Uniqueness (HP)	14,747	0.81	0.09	0.68	0.76	0.82	0.87	0.91
Acquirer inst. block. own.	22,827	0.13	0.13	0.00	0.00	0.10	0.20	0.31
Acquirer staggered board	8,656	0.57	0.49	0	0	1	1	1
Acquirer % outside dir.	8,352	0.72	0.17	0.50	0.63	0.75	0.86	0.89
Acquirer CEO EBC	9,840	0.58	0.29	0.08	0.38	0.64	0.82	0.89
Acquirer age (CRSP)	23,553	15.17	15.87	1	4	10	21	36
Acquirer age (foundation)	23,553	34.39	36.35	5	11	20	42	93
Acquirer RE/TE	22,911	-0.06	2.41	-0.80	-0.01	0.33	0.65	0.89
Acquirer life cycle	19,211	2.44	0.91	1	2	2	3	4
Deal exper.	23,553	4.64	4.41	1	2	3	6	10
Deal exper. 5 yr.	22,091	2.24	2.68	0	0	1	3	5
Target SIC2 HHI	23,355	0.17	0.16	0.04	0.07	0.11	0.19	0.42
Acquirer SIC2 HHI	23,372	0.16	0.16	0.04	0.07	0.10	0.19	0.42
Target SIC2 # of firms	23,355	60.24	54.17	8	21	52	90	109
Acquirer SIC2 # of firms	23,372	60.46	54.59	8	21	53	94	111
Target SIC2 EBIT/Sales	23,355	0.09	0.42	0.02	0.04	0.07	0.11	0.18
Acquirer SIC2 EBIT/Sales	23,372	0.09	0.11	0.02	0.04	0.07	0.11	0.18

Internet Appendix Table 2: M&A sample: descriptive statistics (continued)

	N	**Mean**	**St. Dev.**	**10 pctl.**	**25 pctl.**	**Median**	**75 pctl.**	**90 pctl.**
EW Rival CAR % [−3, +3]	23,280	-0.01	3.49	-3.87	-1.76	-0.06	1.67	3.86
VW Rival CAR % [−3, +3]	23,280	-0.26	3.49	-4.18	-1.95	-0.21	1.48	3.59
EW Customer CAR % [−3, +3]	5,290	-0.17	5.62	-5.23	-2.48	-0.18	2.10	4.93
VW Customer CAR % [−3, +3]	5,290	-0.27	5.01	-5.32	-2.52	-0.21	2.01	4.79
EW Supplier CAR % [−3, +3]	3,388	0.14	9.44	-9.22	-3.99	-0.27	3.51	9.60
VW Supplier CAR % [−3, +3]	3,388	0.03	9.47	-9.51	-4.04	-0.28	3.48	9.40
Combined CAR % [−3, +3]	3,360	1.79	8.00	-6.51	-2.27	1.06	5.52	11.80
Δ OI/Assets [−1, +3]	2,597	-0.11	10.83	-9.50	-3.61	0.15	3.49	9.35
Δ OI/Sales [−1, +3]	2,629	-0.53	7.01	-7.58	-2.86	-0.08	1.71	6.01
Δ OI/Emp. [−1, +3]	2,285	6.63	84.34	-35.05	-11.31	-0.10	11.20	41.60
Target CAR % [−3, +3]	3,361	21.67	20.99	-1.60	7.16	18.75	33.44	49.01
Target CAR % [−42, +3]	3,362	27.84	27.95	-3.35	10.53	24.63	43.16	63.71
Target CAR % [−42, Comp +3]	2,991	25.70	43.58	-24.02	1.24	24.25	50.20	77.51
Offer premium % (4 wk.)	3,249	46.29	32.48	12.20	23.61	39.15	60.98	88.24

Internet Appendix Table 3: Robustness of the year trend in acquirer announcement returns

The table presents the robustness of the baseline results on the trend in acquirer gains to varying definitions of the dependent variable and sample filters. In the first column the only explanatory variable is a linear trend variable that takes the value of zero for the period 1981-1989 and increments by one every subsequent year. In the second column a set of acquirer- and deal-specific control variables is added to the specification. In the third column acquirer industry fixed effects (2-digit SIC level) are added. In the fourth column acquirer industry fixed effects are replaced with acquiring firm fixed effects. In Panel A the dependent variable is Acquirer CAR % [−1, +1], which is the cumulative abnormal return on the acquiring firm stock in the 3-day event window centered on the announcement date. In Panel B the dependent variable is Acquirer CAR % [−2, +2], which is the cumulative abnormal return on the acquiring firm stock in the 5-day event window centered on the announcement date. In Panel C the dependent variable is Acquirer CAR % [−5, +5], which is the cumulative abnormal return on the acquiring firm stock in the 11-day event window centered on the announcement date. In Panel D the dependent variable is acquirer market-adjusted return [−3, +3], which is the cumulative market-adjusted return on the acquiring firm stock in the 7-day event window centered on the announcement date. In Panel E the dependent variable is acquirer dollar gains [−3, +3], which is the cumulative abnormal return on the acquiring firm stock in the 3-day event window centered on the announcement date multiplied by the acquiring firm market capitalization 4 days prior to the announcement. In Panel F the dependent variable is acquirer dollar gains [−3, +3] scaled by deal value. In Panel G the sample is restricted to deals worth at least U.S. $10 million. In Panel H the sample is restricted to deals worth at least 5% of acquirer market capitalization. In Panel I the sample is restricted to acquirers with at least 5 deals in the sample. In Panel J the sample is restricted to deal types "Merger" according to SDC. t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Internet Appendix Table 3: (continued)

	No controls (1)	Controls (2)	Controls + ind. FE (3)	Controls + acq. FE (4)
Panel A: Dependent variable is Acquirer CAR [−1, +1]				
Year trend	0.02	0.05***	0.05***	0.11***
	(1.28)	(4.22)	(3.55)	(5.77)
Panel B: Dependent variable is Acquirer CAR [−2, +2]				
Year trend	0.01	0.05***	0.05***	0.14***
	(1.03)	(3.98)	(3.22)	(6.01)
Panel C: Dependent variable is Acquirer CAR [−5, +5]				
Year trend	0.02	0.06***	0.07***	0.17***
	(1.45)	(4.64)	(4.62)	(6.08)
Panel D: Dependent variable is market-adjusted acquirer return [−3, +3]				
Year trend	0.01	0.05***	0.06***	0.15***
	(0.50)	(4.55)	(3.43)	(5.34)
Panel E: Dependent variable is acquirer dollar gains [−3, +3]				
Year trend	0.32	2.07***	2.18***	6.22**
	(0.53)	(3.39)	(2.98)	(2.31)
Panel F: Dependent variable is acquirer dollar gains [−3, +3] scaled by deal value				
Year trend	0.34*	0.55**	0.54**	1.63**
	(1.92)	(2.54)	(2.34)	(2.70)
Panel G: Sample restricted to deals worth at least U.S. $10 million (N=18,538)				
Year trend	0.03**	0.06***	0.06***	0.15***
	(2.05)	(3.97)	(4.13)	(5.08)
Panel H: Sample restricted to deals worth at least 5% of acquirer market capitalization (N=14,674)				
Year trend	0.03**	0.08***	0.08***	0.20***
	(2.08)	(5.89)	(4.84)	(4.89)
Panel I: Sample restricted to acquirers with at least 5 deals (N=13,814)				
Year trend	0.03*	0.06***	0.06***	0.14***
	(1.98)	(3.86)	(3.71)	(4.83)
Panel J: Sample restricted to deal type "Merger" (N=9,260)				
Year trend	0.04**	0.08***	0.08***	0.19***
	(2.72)	(3.48)	(4.01)	(3.51)

Internet Appendix Table 4: Acquirer announcement returns by deal type

The table presents the results of regression analysis of acquirer announcement returns and related variables for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is Acquirer CAR % [−3, +3], which is the cumulative abnormal return of the acquirer in the 7-day event window centered on the announcement date. The main explanatory variables in all columns are a linear trend variable and its interaction with a particular deal characteristic. All regressions include acquirer- and deal-specific controls and acquiring firm fixed effects. *t*-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Target status (1)	Payment method (2)	Industry relatedness (3)	Geography (4)	Financials (5)	High-tech (6)
Year trend	**0.17*** (5.43)**	**0.18*** (5.00)**	**0.16*** (5.40)**	**0.17*** (5.31)**	**0.16*** (4.65)**	**0.18*** (5.92)**
Year trend x Public target	-0.01 (-0.32)					
Year trend x Cash		-0.02 (-0.88)				
Year trend x Same industry			0.02 (0.73)			
Year trend x Cross-border				-0.01 (-0.50)		
Year trend x Financial					0.10** (2.10)	
Year trend x High-Tech						-0.05 (-1.11)
Controls	YES	YES	YES	YES	YES	YES
Acquirer FEs	YES	YES	YES	YES	YES	YES
N (without singletons)	23,553	23,553	23,553	23,553	23,553	23,553

Internet Appendix Table 5: Does increased speed of market pricing explain the upward trend?

The table presents the results of regression analysis of acquirer announcement period returns for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in column (1) is Positive CAR, which equals Acquirer CAR [−3, +3] when the latter is positive, and zero otherwise. The dependent variable in column (2) is Negative CAR, which equals Acquirer CAR [−3, +3] when the latter is negative, and zero otherwise. The dependent variable in column (3) is acquirer CAR for the period [−3, +21] trading days around the announcement. The dependent variable in column (4) is acquirer CAR for the period [−3, +42] trading days around the announcement. The dependent variable in column (5) is acquirer CAR for the period [−3, +63] trading days around the announcement. All regressions include acquirer- and deal-specific controls and acquiring firm fixed effects. *t*-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Positive CAR (1)	Negative CAR (2)	CAR [−3, +21] (3)	CAR [−3, +42] (4)	CAR [−3, +63] (5)
Year trend	**0.13***** **(5.73)**	**0.07***** **(3.37)**	**0.38***** **(5.96)**	**0.61***** **(5.45)**	**0.81***** **(6.48)**
Controls	YES	YES	YES	YES	YES
Acquirer FEs	YES	YES	YES	YES	YES
N (without singletons)	23,553	23,553	23,553	23,553	23,553

Internet Appendix Table 6: Acquirer announcement returns: effects of prior deal experience

The table presents the results of regression analysis of acquirer announcement returns for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is Acquirer CAR % [−3, +3], which is the cumulative abnormal return of the acquirer in the 7-day event window centered on the announcement date. The main explanatory variable in all columns is a linear trend variable. All regressions include acquirer- and deal-specific controls and acquiring firm fixed effects. The first and third columns report the benchmark year trend effect before additional regressors are added. In the second column the natural logarithm of deal experience is included. In the fourth column the natural logarithm of deal experience in the preceding five years is included. In the fifth column a set of dummies for the number of deals conducted in the previous 5 years is included. *t*-statistics in parentheses are based on standard errors double clustered by acquirer industry (2 digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Baseline (1)	Exper. (2)	Baseline (3)	Exper. 5yr (4)	Exper. 5yr (5)
Year trend	**0.17*** (5.50)**	**0.19*** (4.56)**	**0.17*** (4.69)**	**0.17*** (4.94)**	**0.17*** (4.62)**
Ln (Deal exper.)		-0.32 (-1.28)			
Time since last deal					
Ln (Deal exper. 5 yr)				-0.40** (-2.05)	
1 deal in prior 5 yr					-0.52** (-2.07)
2 deals in prior 5 yr					-0.56* (-1.99)
3 deals in prior 5 yr					-0.76** (-2.74)
4 deals in prior 5 yr					-0.74** (-2.58)
5 deals in prior 5 yr					-0.39 (-0.95)
6-10 deals in prior 5 yr					-0.85** (-2.20)
11-15 deals in prior 5 yr					-0.94 (-1.09)
16-20 deals in prior 5 yr					1.12 (0.94)
21+ deals in prior 5 yr					-0.17 (-0.08)
Controls	YES	YES	YES	YES	YES
Acquirer FEs	YES	YES	YES	YES	YES
N (without singletons)	23,553	23,553	21,959	21,959	21,959

Internet Appendix Table 7: Acquirer announcement returns: age and maturity effects

The table presents the results of regression analysis of acquirer announcement returns for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is Acquirer CAR % [−3, +3], which is the cumulative abnormal return of the acquirer in the 7-day event window centered on the announcement date. The main explanatory variable in all columns is a linear trend variable. All regressions in the table include acquirer- and deal-specific controls. In Panel A, the first two columns additionally include acquirer cohort fixed effects. The second two columns of Panel A include acquirer industry (2-digit SIC level) fixed effects instead of acquirer cohort fixed effects, as well as measures of acquirer age. In Panel B, all regressions include acquiring firm fixed effects. The first and third columns report the benchmark year trend effect before additional regressors are added. In the second column a measure of the mix of earned and contributed capital is added. In the fourth column a measure of acquiring firm life cycle stage is added. *t*-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Age	Cohort FEs (1)	Cohort FEs (2)	Age 1 (3)	Age 2 (4)
Year trend	**0.07*** (5.75)**	**0.06*** (5.72)**	**0.06*** (5.34)**	**0.06*** (5.12)**
Ln (Acquirer age (CRSP))			0.00 (-0.02)	
Ln (Acquirer age (foundation))				0.08 (0.92)
Controls	YES	YES	YES	YES
Acquirer FEs	NO	NO	NO	NO
Cohort (year of birth) FEs	YES	YES	NO	NO
Industry FEs	NO	NO	YES	YES
N (without singletons)	23,553	23,553	23,553	23,553
Panel B: Maturity	**Baseline (1)**	**Maturity 1 (2)**	**Baseline (3)**	**Maturity 2 (4)**
Year trend	**0.16*** (5.85)**	**0.16*** (5.95)**	**0.16*** (4.97)**	**0.16*** (5.26)**
Acquirer RE/TE		-0.04 (-0.67)		
Acquirer Life Cycle				0.06 (0.30)
Controls	YES	YES	YES	YES
Acquirer FEs	YES	YES	YES	YES
N (without singletons)	22,798	22,798	18,953	18,953

Internet Appendix Table 8: Acquirer announcement returns and corporate governance characteristics

The table presents the results of regression analysis of acquirer announcement returns for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is Acquirer CAR % $[-3, +3]$, which is the cumulative abnormal return of the acquirer in the 7-day event window centered on the announcement date. The main explanatory variable in all columns is a linear trend variable and various proxies for acquiring firm governance quality. All regressions include acquirer- and deal-specific controls and acquiring firm fixed effects. The first, third, fifth, and seventh columns report the benchmark year trend effect before additional regressors are added. In the second column acquirer institutional blockholder ownership is added. In the fourth column the fraction of outside directors on the acquiring firm board and its interaction with a public target indicator are added. In the sixth column and indicator variable for acquiring firms with a staggered (classified) board is added. In the eighth column acquiring firm CEO equity-based compensation is added. t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Baseline (1)	Inst. block own. (2)	Baseline (3)	Board indep. (4)	Baseline (5)	Stagg'd board (6)	Baseline (7)	CEO EBC (8)
Year trend	**0.17*** **	**0.18*** **	**0.15*** **	**0.15*** **	**0.13*** **	**0.11*** **	**0.09** **	**0.09** **
	(5.28)	**(5.70)**	**(4.05)**	**(4.12)**	**(3.52)**	**(3.21)**	**(2.09)**	**(2.18)**
Acquirer inst. block. own.		-1.78**						
		(-2.40)						
Acquirer % outside dir.				-0.44				
				(-0.26)				
Acquirer % outside dir. x Public target				2.73*				
				(1.82)				
Acquirer staggered board						-0.64		
						(-1.18)		
Acquirer CEO EBC								0.16
								(0.24)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Acquirer FEs	YES	YES	YES	YES	YES	YES	YES	YES
N (without singletons)	22,704	22,704	7,715	7,715	8,235	8,235	9,280	9,280

Internet Appendix Table 9: Evolution of rival, customer, and supplier reactions

The table presents the results of regression analysis of CARs for rival, cutomer, and suppplier firm portfolios for a sample of acquisitions by U.S. acquirers. Portfolio CARs are equal-weighted in Panel A and value-weighted in Panel B. The dependent variable in the first column is the rival portfolio CAR % [−3, +3], which is the average announcement period abnormal return of corporate rivals of the acquirer, defined as all firms in the same 4-digit SIC industry. In the second column the dependent variable is the corporate customer portfolio CAR % [−3, +3], which is the average announcement period abnormal return of corporate customers of the merging firms, defined as all firms reported as major customers by the bidder and/or the target. In the third column, the dependent variable is the customer portfolio CAR % [−3, +3], which is the announcement period abnormal returns of corporate suppliers of the merging firms, defined as all firms reported as major suppliers by the bidder and/or the target. All regressions include acquirer industry (2-digit SIC level) fixed effects and the natural logarithm of the average portfolio market capitalization (equal-weighted in Panel A, value-weighted in Panel B). The coefficient on the main effect of *Horizontal* is omitted from the table. t-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A	EW Rival CAR [-3, +3] (1)	EW Customer CAR [-3, +3] (2)	EW Supplier CAR [-3, +3] (3)
Year trend	**0.01**	**0.00**	**0.02**
	(0.72)	**(0.12)**	**(0.69)**
Year trend x Horizontal (SIC4)	**0.01**	**0.01**	**-0.03**
	(1.53)	**(0.80)**	**(-1.28)**
Control for portfolio size	YES	YES	YES
Industry FEs	YES	YES	YES
N (without singletons)	23,279	5,283	3,383

Panel B	VW Rival CAR [-3, +3] (1)	VW Customer CAR [-3, +3] (2)	VW Supplier CAR [-3, +3] (3)
Year trend	**0.01***	**0.00**	**0.01**
	(1.94)	**(0.27)**	**(0.31)**
Year trend x Horizontal (SIC4)	**0.01**	**0.01**	**-0.04**
	(0.91)	**(0.71)**	**(-1.58)**
Control for portfolio size	YES	YES	YES
Industry FEs	YES	YES	YES
N (without singletons)	23,279	5,283	3,383

Internet Appendix Table 10: Acquirer announcement returns and industry concentration

The table presents the results of regression analysis of acquirer announcement returns for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is Acquirer CAR % $[-3, +3]$, which is the cumulative abnormal return of the acquirer in the 7-day event window centered on the announcement date. The main explanatory variable in all columns is a linear trend variable. All regressions include acquirer- and deal-specific controls and acquiring firm fixed effects. The first column reports the benchmark year trend effect before additional regressors are added. In the second column the Herfindahl-Hirschman index of the target and acquirer industries are included. In the third column the natural logarithm of the number of firms in the target and acquirer industries are added. In the fourth column the average profit margins in the target and acquirer industries are added. Industries are defined at the 2-digit SIC level. *t*-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Baseline	HHI	# of firms	Profit margin
Year trend	**0.17***** **(5.74)**	**0.18***** **(5.59)**	**0.22***** **(5.91)**	**0.17***** **(5.76)**
Target SIC2 HHI		1.57** (2.54)		
Acquirer SIC2 HHI		-2.69 (-1.52)		
Target SIC2 Ln (# of firms)			-0.2 (-1.47)	
Acquirer SIC2 Ln (# of firms)			1.49*** (2.89)	
Target SIC2 EBIT/Sales				0.14 (0.72)
Acquirer SIC2 EBIT/Sales				-1.4 (-0.85)
Controls	YES	YES	YES	YES
Acquirer FEs	YES	YES	YES	YES
N (without singletons)	23,225	23,225	23,225	23,225

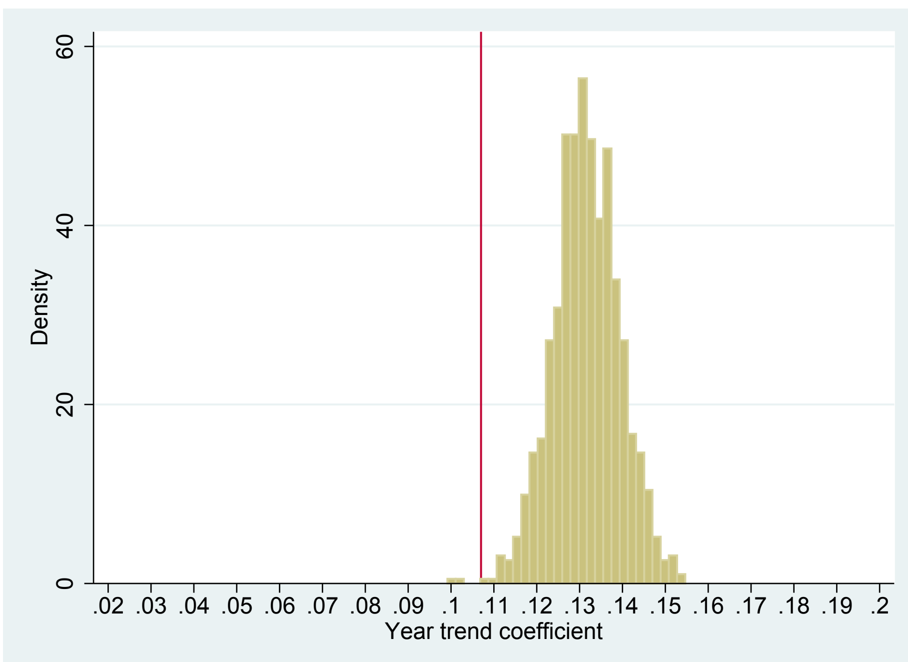
Internet Appendix Table 11: Acquirer announcement returns and M&A advisor fixed effects

The table presents the results of regression analysis of acquirer announcement period returns for a sample of U.S. acquirers over the 1981-2017 period. The dependent variable in all columns is Acquirer CAR % [−3, +3], which is the cumulative abnormal return of the acquirer in the 7-day event window centered on the announcement date. The first column reports the benchmark year trend effect before advisor fixed effects are added. In the second column, advisor fixed effects are added (238 unique non-singleton advisors). The third column reports the year trend effect for the subsample of in-house deals and deals with missing advisor information. All regressions include acquirer- and deal-specific controls and acquiring firm fixed effects. *t*-statistics in parentheses are based on standard errors double clustered by acquirer industry (2-digit SIC level) and year. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively

	Baseline (1)	Advisor FEs (2)	No advisor info (3)
Year trend	**0.13*** **	**0.11* **	**0.15*** **
	(3.08)	**(1.95)**	**(3.95)**
Controls	YES	YES	YES
Acquirer FEs	YES	YES	YES
Advisor FEs	NO	YES	NO
N (without singletons)	6,179	6,179	14,486

Internet Appendix Figure 1: Permutation analysis: Randomizing advisor IDs

The histogram presents the distribution of the coefficient on the *Year trend* variable in a firm fixed effects and advisor fixed effects specification across the permutations. One thousand permutations of the data are performed: each time advisor identifiers are randomly shuffled across observations. The vertical red line indicates the coefficient on the *Year trend* variable in the firm fixed effects and advisor fixed effects specification run on the actual data.



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