Competitive approaches in mergers and acquisitions

Tina Oreski*

Abstract

This paper uses mergers and acquisitions (M&A) and textual analysis of firms' financial filings to show that competitive approach constitutes an important determinant of firms' investment decisions. The analysis reveals that becoming an acquirer or a target depends on the competitive approach. Moreover, M&A deals are more likely between companies implementing the same competitive approach. Those deals yield higher combined announcement returns, asset and sales growth. The same approach effect is stronger in a highly competitive environment and within an industry, suggesting that acquirer and target misalignment in competitive approaches constraints the optimal response to investment opportunities and market threats.

Keywords: Mergers and Acquisitions, Competitive Approach, Product Life Cycle, Competition, Textual Analysis

*ESCP Business School, Corso Unione Sovietica, 218 bis, 10134 Turin, Italy, email: toreski@escp.eu. I would like to thank Bruno Biais (discussant), Francesco D'Acunto, Francois Degeorge, Zoran Filipovic, Vyacheslav Fos, Laurent Fresard, Zongbo Huang (discussant), Gael Imad'Eddine (discussant), Gordon Phillips, Davide Tedeschini, and Paolo Volpin (discussant). This paper also benefited from comments by seminar participants at BI Oslo, Boston College, ESCP, George Washington University, Indiana University, University of Bern, University of Lugano, University of St. Gallen, and conference participants at SFI research days 2019, 17th Corporate Finance Day, Nova Ph.D. Finance event 2021, SWFA 2021, SGF 2021, AFFI 2021, AFA 2022. This work was supported by Swiss National Science Foundation [P1TIP1_187842].

1 Introduction

Products move through life cycles.[1] Nevertheless, two companies can choose different life cycle curves for a similar product. On one side of the spectrum are companies aiming to be the first on the market with new products and innovations, while on the other side are companies specializing in cheaper versions when the products are already standardized and their demand well established (Klepper, 1996). Hence, one firm's product life cycle can begin before and have a differently shaped curve than the other firm's product life cycle. I refer to these differences in the companies' product life cycles as competitive approaches or strategies.[2] Competitive approaches directly affect firms' resource allocation, cash flows, and investments. Yet, financial economists have largely ignored this relation. This paper eliminates the gap by empirically examining whether firms' competitive approaches affect one of their biggest investment decisions: mergers and acquisitions (M&A).

In M&A, the transaction incidence and the deal performance depend on both the acquirer and the target company. The finance literature has shown the positive impact of the overlap in the product, technology, human capital, and culture dimension (Hoberg and Phillips, 2010; Bena and Li, 2014; Lee et al., 2018; Bereskin et al., 2018; Li et al., 2020). However, none of these studies explores how M&A deals depend on acquirers' and target firms' competitive approaches and their similarities.

Firms with different competitive approaches experience different cash flows and face different risks (Dickinson, 2011). Therefore, the acquirer's management can better predict the future cash flows of the same approach target company than of a different approach target. The importance is especially visible when a new investment opportunity or market threat arises because the management's optimal decision changes depending if the company is an innovating firm starting the product life cycle early or a firm entering the market when the product is already standardized. Consequently, the main hypothesis of the paper is that misalignment between target and bidder competitive approaches constrains the merged company's optimal response to investment opportunities and market threats and diminishes potential M&A synergies.

[1]See, e.g., Abernathy and Utterback (1978); Hoberg and Maksimovic (2022); Hajda and Nikolov (2022)
[2]Following Caves (1980); Gimeno and Woo (1996); Utterback and Abernathy (1975), among others.

To test the hypothesis, I require an estimate of companies' competitive approaches. The literature categorizes companies into four competitive approaches. Performance-maximizing firms attempt to be the first to introduce innovative products or services; sales-maximizing companies observe the innovations on the market and are prompt to adapt and offer new product variations and features quickly; cost-minimizing companies emphasize efficiency in cost production and enter the market later with simpler and less expensive versions; stuck-in-the-middle companies try to compete on multiple of the previous approaches, but they do not manage to apply any of them consistently (Utterback and Abernathy, 1975; Kim and Lim, 1988).[3]

To illustrate the concept, imagine an automotive industry with four companies, as depicted in Figure 1. Company A introduces an innovative car with parking sensors at time 0. Its innovation is unique on the market until time 2 when Company B offers a car with parking sensors. Company C enters the market at a later stage, at time 5. Its advantage compared to Companies A and B lies in the cheaper production of cars with parking sensors. At this stage, Company D also tries to compete by offering cheaper products. When the sales of the car with parking sensors drop sufficiently at time 6, Company A launches another innovation: a car with parking cameras. Again, it is the only company in the industry with the new product until Company B introduces a car with parking cameras at time 8. For their car with parking cameras, Company D changes its competitive approach and enters the market at time 8, like Company B. Competitive approaches can be understood as the shift in time of the product life cycles- Company A applies the performance-maximizing approach, Company B the sales-maximizing approach, Company C the cost-minimizing approach, and Company D applies different approaches across different products and it is stuck-in-the-middle because the cash flows from one project do not align with the needs of the other project.

[Insert Figure 1 about Here]

Thus, Utterback and Abernathy (1975) model the change in competitive approaches with firms' product life cycles. I build on their model and employ the product life cycle as the starting point to measure the competitive approach. Following Hoberg and Maksimovic (2022), I exploit the textual

[3]The first three categories closely follow the classification of Utterback and Abernathy (1975). Following Kim and Lim (1988), Porter (1980), and Miles et al. (1978), I define an additional group, stuck-in-the-middle companies.

analysis of 10-K financial statements to calculate the product life cycle. The procedure maps each company to a four-element vector every year that sums up to one: product innovation, process innovation, stability, and product discontinuation. Every product life cycle expresses the proportion of a company's products in a particular stage, which varies significantly across approaches. Therefore, I propose an additional step to measure the competitive approach: comparing a firm's product life cycle with its most similar firms and detecting the product life cycle that obtains the highest ranking within the matching industry. The intuition is that the strongest product life cycle emphasizes companies' competitive focus (on average, Company A prioritizes introducing innovative products compared to Companies B and C). This step embeds the proxy's relative aspect: a firm's competitive approach is measured in relation only to its similar firms. As a result, companies are flagged as applying performance-maximizing, sales-maximizing, cost-minimizing, or stuck-in-the-middle competitive approaches.

Companies oriented toward the performance-maximizing approach are the youngest, grow the fastest, and reserve the biggest part of their sales for research and development (R&D), while companies that do not consistently apply any of the first three approaches are the oldest, have the lowest growth rate, and the smallest market-to-book (MB) ratio. The combination of traditional life cycle proxies (asset size, company's age, retained earnings over assets) explains up to 0.05 of the variation in the companies' competitive orientation.[4] This result suggests that the competitive approach carries different information not absorbed by the life cycle proxies, which can bolster our understanding of the companies' investment decisions.

With the proxy for companies' competitive approaches in hand, I report three central findings. First, I document that in US public M&A deals between 1995 and 2017, both target and acquirer firms spread through all the competitive groups. Nonetheless, performance-maximizing companies realize the highest probability of becoming both acquirers and targets. The presence of targets across all the groups demonstrates that all acquirers are not driven by one acquisition motive; they pursue different goals through M&A. Second, the odds of a transaction for companies with the same competitive traits are twice as large as the odds for companies that belong to dissimilar approaches. This acquirer-target pair pattern reveals that firms anticipate the obstacles stemming from a partner

[4]The results are presented in Appendix A.

with a different competitive posture and opt for one with the same approach, for which managers possess more knowledge and experience. Third, deals with competitive approach overlap earn, on average, 87 basis points higher combined announcement returns, and the acquirers' assets and sales increase significantly after the acquisition compared with the companies that bought a target with a different approach. The analysis supports that acquirers buying competitively related target firms outperform other acquirers.

Next, I test the driving force behind the results: the competitive approach misalignment induces a company's suboptimal response to investment and business opportunities because the manager lacks experience and knowledge in managing a company with a different resource allocation. Eliminating these potential difficulties and reacting promptly should be particularly relevant in a high-competition environment, as intense competition demands a company's swift response due to the predatory risk (Haushalter et al., 2007; Valta, 2012). The separation of the sample into low and highly competitive, using the TNIC Herfindahl-Hirschman index (HHI) by Hoberg and Phillips (2016) and the product fluidity measure by Hoberg et al. (2014), upholds that companies in highly competitive industries exhibit a higher likelihood of acquiring a company with the same competitive approach. Moreover, competitive differences between a target and a bidder in diversifying acquisitions might not be detrimental since such a merger could involve two different settings where the requirements for success vary (Ramaswamy, 1997). Therefore, I examine whether the negative impact of competitive dissimilarity is more pronounced in the same industry acquisitions. The results provide strong support for the claim. These findings corroborate that managers better understand investment opportunities and threats for companies implementing the same competitive approach, resulting in better deal performance.

I complement the analysis with several robustness tests. I explicitly consider whether the results are driven by the traditional life cycle proxies and variables used in previous studies to predict M&A participation and abnormal returns, including size, age, profitability, market-to-book (MB) ratio, debt, and R&D expenses. Additionally, I verify the combined announcement return results with the market and Fama and French (1993, 1996) three-factor models. I further present the results including product-market similarity (Hoberg and Phillips, 2010), innovation (Bena and Li, 2014), and organizational culture (Li et al., 2020) variables. The main findings withstand those robustness checks. In summary, the main contribution of the paper is to show that competitive approaches affect firm investment decisions.

2 Related literature

This paper speaks primarily to the literature studying similarities and synergies in M&A. Rhodes-Kropf and Robinson (2008) formulate the assortative matching concept in M&A: in economic terms, acquirers and targets are similar (i.e., like buys like). They provide evidence that most transactions involve high market-to-book (MB) valuation firms purchasing other high-valuation firms and low-valuation firms acquiring other low-valuation firms. Hoberg and Phillips (2010) examine whether firms harness product market synergies through asset complementarities in M&A. They demonstrate that firms with similar product market language reach higher transaction likelihood and higher stock returns. Bena and Li (2014) conclude that technological overlap between firm pairs positively relates to transaction incidence and merger outcomes. Lee et al. (2018) find that merger returns and postmerger performance are higher when firms have related human capital. Bereskin et al. (2018) and Li et al. (2020) show that corporate culture relatedness contributes to both the likelihood and benefits of mergers. Chen et al. (2020) emphasize that reducing search frictions increases the likelihood of complementary mergers and postmerger synergistic value. I document that synergies arising from the similarity in competitive approaches constitute a strong determinant of public M&A decisions.

The paper also adds to the fast-growing research in finance that employs textual analysis for hypothesis testing. Hoberg and Phillips (2016) generate a new set of industries based on text analysis of firm 10-K product descriptions. Eaton et al. (2022) use the classification to show it better explains investment banks' choice of peers in comparable companies analysis in M&A than fixed industry classifications. Buehlmaier and Whited (2018) construct a measure of financial constraints using textual analysis of firms' annual reports and conclude that excess returns are higher for financially constrained firms. Cohen et al. (2020) underline that changes to the language and construction of 10-Ks and 10-Qs predict future earnings, profitability, and future firm-level bankruptcies. Hoberg and Maksimovic (2022) generate a new proxy for the product life cycle based on the textual analysis of 10-K filings. Based on the same measure, Chen et al. (2020) provide evidence that firms with more exposure to the mature life cycle stage disclose substantially more details. In contrast, firms in the early stage of the life cycle strongly favor secrecy, consistent with inward-focused organic investment and mitigation of competitive threats. I propose a measure of the competitive approach based on the Hoberg and Maksimovic (2022) and Chen et al. (2020) product life cycle measure.

3 Data

I construct the sample from four data sources: Thomson One SDC for M&A, the Center for Research in Security Prices (CRSP) for price and return data, Compustat for the companies' balance sheet data, and US Securities and Exchange Commission Electronic Data Gathering, Analysis, and Retrieval (SEC EDGAR) database for financial statements.

In Compustat, I exclude all the companies located outside the US, corporations with missing assets, and financial companies and utilities (Standard Industrial Classification codes 4900–4999 and 6000–6999). I map Compustat data to machine-readable 10-K documents, which yields 89,069 firm-year observations from 1994 to 2017. I extract all completed M&A with the date announced between January 1st, 1995 and December 31st, 2017, and I impose the following criteria: the acquirers are US public firms; the targets are US public firms and their subsidiaries; the deal is completed, the acquirer holds less than 50% of the target before the transaction and more than 50% after the transaction; neither the acquirer nor the target belongs to the financial sector because their balance sheets are very different from other firms or the utility sector since they are heavily regulated; date effective, percentage of shares owned after the transaction, percentage of shares acquired, and announcement date are non-missing; the company did not acquire another firm 120 days before the announcement day to ensure the estimation window of cumulative abnormal returns does not include other acquisitions.

After merging M&A data with company-year observations and excluding companies with missing assets, EBITDA, debt, MB ratio, and competitive approach (both for the acquirers and the targets), the procedure leaves me with 3,104 acquirer-target pairs. Table 1 tabulates the acquisitions during the sample period into public or subsidiary and cash, stock, or mixed deals. The number of acquisitions varies substantially over time, with many in the second half of the 1990s. Subsidiary acquisitions are more common than the acquisitions of entire public companies. Cash-only deals dominate over stock-only deals, with an average of 40% of the total number of transactions.

[Insert Table 1 about Here]

Following the existing literature, the other variables used throughout the paper are constructed as follows. *Assets* is defined as a natural logarithm of book assets (Compustat item AT). *Age* is the natural logarithm of a firm's age, measured as the number of years in the Compustat database. *Debt* represents the ratio of long-term debt to assets (DLTT/AT). *R&D* are research and development costs (XRD/sale); missing values are set to 0. *EBITDA* is defined as a firm's profitability (EBITDA/AT). *MB* stands for market-to-book ratio, calculated as the market value of the firm to total book asset value ((AT-CEQ+PRCC_F*CSHO)/AT), where the market value is proxied as the book value of assets less book value of common equity plus the market value of equity (equal to the stock price at the fiscal year-close times the number of common shares outstanding).

Table 2 presents descriptive statistics for acquirers and targets in the sample. Both types of companies are large US firms, with a mean asset size of over five billion US dollars. Acquirers achieve higher profitability and higher MB ratio than the targets, while targets spend more on R&D.

[Insert Table 2 about Here]

4 The competitive approach measure

To find a competitive approach proxy applicable to a broader range of companies, I follow Utterback and Abernathy (1975). They model that products develop over time in a predictable manner (with initial emphasis on product performance, then the emphasis moves to product variety, and finally to product standardization and costs) and that one can distinguish competitive approaches from companies' products. Ergo, I apply the product life cycle as a starting point to measure firms' competitive approaches.

To measure a firm's product life cycle, I build on a recent finance literature approach using textual analysis of firms' financial statements (Hoberg and Maksimovic, 2022; Chen et al., 2020). Unlike the other proposed measures, this methodology reflects that companies contain multiple products in different life cycle stages. I start by calculating the product life cycle by Hoberg and Maksimovic (2022), which implements textual analysis on 10-K financial statements.[5] The first step of the calculation employs Web crawling and text parsing algorithms to construct a database of machine-readable SEC EDGAR 10-K annual fillings from 1994 to 2017. I search the EDGAR database for filings that appear as "10-K","10-K405","10KSB", "10KSB40", or "10-KT". Then, I implement anchor-phrase methods to extract paragraphs from 10-K filings related to a company's specific life cycle. Appendix B describes the procedure in detail. I deviate from the exact Hoberg and Maksimovic (2022) procedure in two ways: first, I delete the names of the cities in the US starting with the word "new" (for example, New York, New Orleans), as these cities might interfere with the first product life cycle; second, I retain the paragraphs including phrases "research and development" and "capital expenditure" because those paragraphs can contain valuable life cycle information.[6] I normalize the product life cycle exposure vector with the four individual paragraph counts by dividing each number by the total paragraph counts.

The procedure gives a four-element vector for each company in each year that sums up to one, and the elements express the fraction of the firm's products allotted to each of the four stages by Abernathy and Utterback (1978): (1) product innovation (Life1), (2) process innovation (Life2), (3) stability and maturity (Life3), and (4) product discontinuation (Life4). To measure the competitive approach, I calculate for each company-year the percentile ranking of every product life cycle within the industry[7] in a three-year period.[8] The product life cycle with the highest ranking denotes the company's competitive approach.[9] That way, a company's approach is determined with respect to

[5]Public companies must file the annual report on Form 10-K, providing a comprehensive overview of the company's business and financial condition and including audited financial statements. Under the regulation S-K, Item 101, the companies are obliged to describe the business done, the principal products produced and services and a description of the status of a product or segment.

[6]The correlation coefficients between the Hoberg and Maksimovic (2022) life cycles and the life cycles calculated in this paper range between 0.84 and 0.95

[7]Industry in the main results is defined as a 2-digit NAICS industry. However, the results hold by specifying the industry to be 3-digit NAICS, 2-digit or 3-digit SIC, and identifying the nearest rivals as in Hoberg and Phillips (2016).

[8]I set the product phase with less than 15% to zero percentile to avoid classifying companies into stages that do not represent a relevant part of the portfolio of products.

[9]In the unreported results, I varied the percentage from 10 to 25, and the results remain similar.

its similar firms and not to the whole population of firms.

As an illustrative example, a company with three consecutive product life cycle vectors of [0.69 0.21 0.03 0.07] in 2006, [0.70 0.27 0.01 0.02] in 2007, and [0.71 0.24 0 0.06] in 2008, averages [0.70 0.24 0.01 0.05] for the three years. Based on the average, the company's corresponding percentiles for 2008 within its industry are [95 28 0 0], and it is assigned to the performance-maximizing group. Similarly, a company fits the cost minimization or sales-maximizing approach if the highest percentile accompanies the second or third product phase, respectively. I sort a firm as a stuck-in-the-middle whenever the firm's dominant product life cycle percentile is the fourth phase, as those companies do not manage to apply any of the first three approaches consistently, and they end up with more obsolete products (Porter, 1980). Thereby, the competitive approach measure indicates the company's highest product life cycle percentile within its industry in a three-year period, and it designates companies into performance-maximizing, cost-minimizing, sales-maximizing, or stuck-in-the-middle groups.

Performance-maximizing approach is seen in the early stages of the product life cycle. These companies emphasize differentiated products and services based on R&D and innovations. They charge higher prices due to enhanced quality and performance. Sales-maximizing companies rely on greater diffusion of their current products or services and stable relationship with their customers and suppliers. They watch others innovate and are prompt to adapt and offer new product variations and features quickly. The emphasis is placed on expanding sales and gaining market share. As the product life cycle evolves, product variety tends to be reduced, and the product becomes standardized. Companies applying the cost-minimizing approach focus on process innovations and efficiency in the manufacturing and distribution of products to reach low product prices. Finally, stuck-in-the-middle companies struggle to apply any of the first three approaches consistently and end up with more obsolete products.

Table 3 summarizes the average firms' characteristics in each competitive group. Performance-maximizing companies are the youngest, grow the fastest, maintain the lowest debt ratio, allocate the biggest part of their sales to R&D, and realize the highest average patent value.[10] Consistent

[10] Patent data come from Kogan et al. (2017) The dollar value of a patent is based on the stock market reaction on the patent issue date

with the findings of Kogan et al. (2017) that large firms tend to file more patents, sales-maximizing firms obtain the highest number of patents per year. Cost-minimizing companies hold the highest debt percentage and are slightly older than sales-maximizing firms. Stuck-in-the-middle firms are the oldest, have the lowest growth rate, and have the smallest MB ratio. In addition, product life cycle phases demonstrate that, on average, firms own products in all life phases. Still, performance-maximizing firms produce the highest percentage of innovative products, sales-maximizing companies load predominantly on the third product life cycle stage, while cost-minimizing companies focus on lowering the cost of production. The product life cycle vector for stuck-in-the-middle firms supports the idea that the new proxy identifies the firm competitive position relative to the other companies in the same industry. Even though stuck-in-the-middle firms have the highest percentage of obsolete products among all firms, they own more cost-minimizing products in absolute terms.

[Insert Table 3 about Here]

4.1 Dynamics of competitive approaches

Figure 2 depicts the ratio of firm competitive approaches over the years for the entire sample of firms, including acquirers, targets, and firms that did not transact. The proportion of performance-maximizing firms is the lowest at the beginning of the sample and the highest at the end, reaching 34% in 2017. Part of the growth lies in the increasing fraction (9% to 43%) of high-tech companies in the sample.[11] In the same period, cost-minimizing corporations comprise between 26% and 37%, and sales-maximizing firms vary between 25% and 31%. Stuck-in-the-middle public companies are the least represented category, with a peak of 20% after the financial crisis.

[Insert Figure 2 about Here]

Table 4 discloses the other type of dynamics: the mobility between the approaches in a one-year horizon.[12] It outlines that firms primarily remain in the same competitive group. Still, the

[11] I use the official definition of high-tech industries offered by the United States Department of Commerce. High-tech companies are defined as firms with three-digit SIC industry codes: 283, 357, 366, 382, 384, and 737. The classification is also applied in Brown et al. (2009).

[12] The table does not include the delistings because of liquidations and dropped firms (CRSP codes 400-599). During

lack of zero loadings in all the transition matrices confirms that companies may progress from the current to any of the three remaining competitive approaches. The result emphasizes the difference between the product life cycle and the competitive approach. While companies' products always move from the innovation to the obsolescence phase, they can optionally change their competitive approach depending on the competition and prospects. One of the leading examples of the competitive approach changes is Apple in 1995. Twenty years after its foundation, Apple's market share stagnated, it incurred financial loss and was forced to lay off some of its employees. Trying to solve the problems, the company hired Steve Jobs as the CEO, which led to a series of innovations (iMac, Mac OS, iPhone, etc.), and eventually positioned Apple as one of the world's most valuable companies.

[Insert Table 4 about Here]

The changes from the performance-maximizing to the stuck-in-the-middle approaches and vice versa within one year form the smallest fraction of transitions. They mainly occur as a consequence of firm restructuring and selling the least profitable segments. For example, before 1999, the management team of Ultrak company (CIK:318259) emphasized acquisitions to obtain new products, integrated systems, experienced personnel, channels of distribution, and new geographic territories. However, in 2000, Ultrak replaced the management team and referred to the transformation from a distributorship to a technology-based company as challenging, generating losses and resulting in downsizing the workforce. This short description elucidates why, accounting for other industry participants in the same year, Ultrak company is labeled as a performance-maximizing firm in 1999, while it is flagged as a stuck-in-the-middle company from 2000 to 2004.

5 Results

The competitive approach determines the product life cycle curves of firms' products, with the ultimate goal of maximizing firms' values and creating a competitive advantage. Therefore, it has a direct bearing on firms' investment decisions. This section analyzes this hypothesis in several steps.

the sample years, 3.6% of the performance-maximizing firms and 5% of the stuck-in-the-middle firms delisted in the following year for those reasons.

The first two steps test whether the probability of becoming an acquirer or a target is related to companies' approaches and if so, which companies become acquirers and which become targets? Do all acquirers and targets belong to one approach, or are they dispersed across different approaches? The third step investigates the acquirers and the target competitive pairs to understand whether acquirers select targets that match their competitive approaches or whether all acquirers focus on the targets with one competitive type.

The driving mechanism is that the divergence between the competitive approaches in M&A deals acts as a constraint to a company's optimal response to business and investment opportunities because the acquiring firm's manager lacks knowledge and experience about the target's resource allocation and competitive conditions (Harrison et al., 2017). The results in line with the predictions should pinpoint that acquirers seek out targets with the same competitive approach and that those deals reap higher synergies. Hence, the fourth step turns to the performance of the same and different competitive approach deals. Furthermore, if the acquiring managers lack the knowledge and experience to manage a firm with a different competitive approach, I expect the effect to be stronger in a high-competition environment compared to a low-competition environment, as the timely and optimal reactions to business threats and opportunities are more important with intense competition (Haushalter et al., 2007; Valta, 2012). Also, success in different industries depends on different requirements, which lessens the necessary fit in diversifying acquisitions (Ramaswamy, 1997). On this ground, I study the likelihood of acquiring a company with the same competitive approach in low and high-competition environments and in related and diversifying deals.

5.1 Acquirers' competitive approaches

I begin by inspecting the acquirers' competitive traits. Figure 3 illustrates the ratio of acquirers' competitive approaches over the years. Acquirers do not cluster in one competitive group but spread through all the groups. The result implies that companies continuously evaluate external investment opportunities and do not have to exhaust their internal projects before acquiring other companies.

[Insert Figure 3 about Here]

For a direct test, I run a conditional logistic regression, following Bena and Li (2014) for firm i, deal m, and year t:

$$\begin{aligned} AcquirerFirm_{i,m,t} = \alpha + \beta_1 Performance_{i,t-1} + \beta_2 Sales_{i,t-1} + \beta_3 Stuck_{i,t-1} + \\ \delta_1 X_{i,t-1} + \eta_m + \epsilon_{i,m,t}, \end{aligned} \tag{1}$$

where the dependent variable, $AcquirerFirm$, is an indicator variable equal to one if the firm acquires another company in a given year, and zero otherwise. Since a company fits only one of the four approaches, the cost-minimizing group acts as the reference category, and the coefficients should be interpreted in relation to the cost-minimizing group.[13] X is a set of control variables known to predict the probability of becoming a target or an acquirer firm: assets, age, debt, MB ratio, profitability, and R&D. η is the fixed effect for each acquirer (target firm) and its control acquirers (control target firms). All variables are measured at the fiscal year-end immediately prior to the acquisition announcement date. Column 1 includes only the indicator variables for the performance-maximizing ($Performance$), sales-maximizing ($Sales$), and stuck-in-the-middle ($Stuck$) firms, whereas Column 2 also incorporates the control variables.

[Insert Table 5 about Here]

For each deal, there is one observation for the acquirer and multiple observations for the control acquirer group. To form the control group for each acquirer, I find up to five firms within the same industry and in the same year that did not participate in the acquisitions (neither as an acquirer nor as a target firm) in the last three years and that are most similar based on the propensity-matching score. Table 5 Columns 1 and 2 match on firms' assets and Column 3 matches on firms' assets and age.

The first three columns report the coefficient estimates and imply that cost-minimizing companies have the lowest probability of becoming acquirers. After considering other explanatory variables in Columns 2 and 3, performance-maximizing and sales-maximizing companies are associated with the highest probability of becoming acquirers. The odds of becoming an acquirer for the performance-maximizing (sales-maximizing) companies are between 2.61 and 1.77 (1.25 and

[13] Selecting the cost-minimizing group is arbitrary.

1.12) times as large as the odds for the cost-minimizing companies.[14] The likelihood of becoming an acquirer compared with the closest companies by propensity matching score is positively related to lower age, lower debt ratio, higher profitability, and higher R&D. In summary, this section substantiates that acquirers choose different competitive approaches, which hints that they should also aim for different target firms.

5.2 Target firms' competitive approaches

The paper is articulated around the idea that acquirers consider targets' competitive approaches in their M&A decisions. To test this hypothesis, Figure 4 plots the fraction of the target firms in distinct competitive groups over the years. Targets are also located in all the groups.

[Insert Figure 4 about Here]

In the next step, I repeat the conditional logistic regression in Equation 1 for firm i, deal m, and year t:

$$\begin{aligned} TargetFirm_{i,m,t} = \alpha + \beta_1 Performance_{i,t-1} + \beta_2 Sales_{i,t-1} + \beta_3 Stuck_{i,t-1} + \\ \delta_2 X_{i,t-1} + \eta_m + \epsilon_{i,m,t} \end{aligned} \tag{2}$$

where the dependent variable, $TargetFirm$, is a binary variable equal to one if the firm or one of its subsidiaries was acquired by another public company in that year, and zero otherwise. Cost-minimizing companies again serve as the reference category, and all other variables remain specified as in Equation 1. The procedure to determine the control target group follows the steps described for the acquirer groups. Table 5 Columns 4 and 5 match on firms' assets, and Column 6 matches on firms' assets and age.

The last three columns record coefficient estimates from the conditional logit regression. Across specifications, performance-maximizing companies are associated with the highest probability of becoming targets, significant at the 1% level. For performance-maximizing companies, the odds of becoming a target are between 3.18 and 1.98 times as large as the odds for companies pursuing the

[14] It is important to note that the sample includes public, but not private targets as it is the case in Hoberg and Maksimovic (2022).

cost-minimizing approach. The results support the hypothesis that the target firm's competitive approach shapes the acquiring firm's focus of the search, and it rules out that the bulk of target firms hoards in one group (for example, the performance-maximizing approach). Compared with the closest firms by the propensity score, younger, less profitable, with less debt, and higher R&D companies are positively related to the probability of becoming targets.

5.3 Competitive pairs

After demonstrating that both acquirers' and targets' competitive approaches matter in M&A deals, the next step analyzes the acquirer-target pairs. Table 6 partitions the deals on the acquirer and target competitive groups. It establishes that acquirers and targets cover all the groups, but one pattern stands out in the table: companies mainly acquire firms with the same approach; the percentage varies from 30% for stuck-in-the-middle firms to 48% for performance-maximizing firms. Table 7 presents deal examples for each acquirer-target competitive pair.[15]

[Insert Table 6 about Here]

[Insert Table 7 about Here]

As the number of companies in different approaches does not have to be equal, I investigate this pattern in a more formal setting. Table 8 shows coefficient estimates from the conditional logit regression for firms i and j, deal m, and year t:

$$RealPair_{i,j,m,t} = \alpha + \beta SameApproach_{i,j,t-1} + \delta_1 X_{i,t-1} + \delta_2 X_{j,t-1} + \eta_m + \epsilon_{i,j,m,t}, \qquad (3)$$

where the dependent variable, $RealPair$, is a dummy variable equal to one if a given company pair is a true acquirer-target pair in a given year and zero otherwise. For each deal, there is one observation for the acquirer (target firm) and up to five observations for the control acquirers (target firms). I select the control sample based on the propensity-matching score within the same

[15] The sample of target companies includes both public companies and their subsidiaries. Subsidiary companies are already organized according to the resource allocation of the parent company, which, in the same approach deals, is similar to the acquirers' resource allocation.

industry and the same year, as in Table 5. The coefficient of interest is related to *SameApproach*, a dummy variable equal to one if a company pair overlaps in the approach and zero otherwise. Table 8 Column 1 and 2 match on firm size, while Column 3 matches additionally on firm age. Column 1 includes only the variable *SameApproach* and Columns 2 and 3 saturate the model with control variables.

[Insert Table 8 about Here]

In all the columns, *SameApproach* exhibits a positive and significant coefficient at the 1% level, indicating the same competitive approach leads to merger pairing. For the companies that pursue the same approach, the odds of a transaction are more than two times as large as the odds for companies that belong to different groups. The other control variables show predictable signs. Table 8 lends strong support for the competitive approach synergies.

Collectively, I present a large body of evidence and tests that the target firm's competitive approach forms an important factor in M&A decisions. But what are the benefits of acquiring a company with the same competitive approach?

5.4 Ex-post outcomes

I examine the benefits of the same approach deals through financial and real ex-post outcomes. Table 9 tests the financial outcomes by estimating combined acquirer and target announcement return for acquirer i, target j, acquirer's industry z, year t:

$$\begin{aligned} CombinedReturn_{i,j,z,t} = \alpha + \beta SameApproach_{i,j,t-1} + \gamma DealCharateristics_{i,j} \\ + \delta_1 X_{i,t-1} + \delta_2 X_{j,t-1} + \mu_z + \theta_t, \end{aligned} \tag{4}$$

where Deal Characteristics include: a subsidiary target indicator, *Subsidiary*, as the long-standing literature attests different CAR based on the status of the target; dummies for stock-only and cash-only deals, *CashDeal* and *StockDeal*, to control for acquisitions of targets paid only with stocks or cash; relative deal size, $RelativeSize$, since target size affects the acquirer's returns; industry relatedness of the acquisition, $DiffInd$, to capture that diversifying acquisitions have been found to destroy value (Morck et al., 1990; Andrade et al., 2001; Travlos, 1987; Fuller et al., 2002).

[Insert Table 9 about Here]

I implement the Carhart (1997) four-factor model to calculate the 3-day cumulative abnormal return (CAR) for both acquirers and targets during the window encompassed by event dates [-1,1], where event day 0 is the acquisition announcement date. The estimation window covers a 120-day period, from event day -130 to event day -11, as suggested in Campbell et al. (1997). Combined returns are weighted by the market capitalization of both participants ten days before the announcement day. The combined return and continuous control variables are winsorized at the 1st and 99th percentiles to alleviate the impact of outliers. I have downloaded the daily factor data from Kenneth R. French's website.

The average acquirers' and targets' CAR for the overall sample are 0.87% and 10.57%, respectively. The mean bidder CAR for public targets amounts to -0.42%, while for the targets equals 25.53%. The average bidder CAR for subsidiaries is 1.72%, while targets experience an increase of 1.48%. The combined return averages 1.24% for the entire sample, 2.29% for public, and 0.63% for subsidiary target firms. The estimates are consistent with prior work (Maksimovic et al. (2011), Alexandridis et al. (2017), Filipovic and Wagner (2021)).

Table 9 Column 1 includes only the variable of interest *SameApproach*, while Column 2 also builds in the deal characteristics and acquirer i and target j control variables. All the columns add industry and year fixed effects to account for the unobserved industry and time-specific shocks. The coefficient of *SameApproach* in both columns is positive and statistically significant at the 1% level, suggesting that deals where the acquirer and the target belong to the same competitive group yield, on average, 87 basis points higher combined announcement returns than the pairs with different stages. Control variables exhibit predictable signs. Thus, the combined return analysis authenticates the competitive approach synergies.

Next, I track whether the financial value creation of acquiring a company with the same competitive approach is accompanied by real post-acquisition gains, particularly asset and sales growth.

The challenge is that asset and sales growth may endogenously relate to merger and acquisition decisions. To address these concerns, I exploit a quasi-experiment, following Seru (2014) and Bena and Li (2014), where I compare the firms that withdrew their acquisitions of companies in the same (different) competitive approach with the firms that acquired a target company with the same (different) competitive approach. In the withdrawn sample, both the acquirer and the target are publicly listed US firms, and neither the acquirer nor the target belongs to the financial sector or utilities. After merging both acquirers and targets of the withdrawn acquisitions with the competitive approach data, the procedure results in 801 withdrawn acquisitions. The withdrawn acquisitions occur during the same year as the matched effective acquisitions, and the acquirers of the two acquisitions have the same age.[16] An additional condition for the treatment group is that the companies did not buy another public company or a subsidiary of a public company three years before the focal acquisition attempt. This restriction shrinks the sample of effective acquisitions from 3104 to 2088 deals. After merging with the control sample, the final sample consists of 749 acquisition pairs, 557 pairs with the same approach, and 192 pairs with a different approach. I adopt the three-year period around the announcement to inspect the parallel trend assumption of the difference-in-differences analysis (DiD). This step helps mitigate concerns that differences between the treated and the control group are not constant before the acquisition.

Figure 5 verifies the parallel trend assumption for assets, and Appendix C focuses on the parallel trend in sales. Panel A in Figure 5 plots the average asset size for the treatment and control subsample for the deals with the same approach, while Panel B plots the deals where the acquirer and the target have different approaches. The time spans from three years before the announcement to three years after the announcement. Prior to the deal announcement, the evolution of the two groups in both subsamples is largely parallel. The gray area on the graphs marks the year of acquisition. The surge in the assets of the effective acquisitions in that year is mostly mechanical (A+B>A); however, the analysis concentrates on the period after the acquisition. After the acquisition, the two lines separate in Panel A, and they remain parallel in Panel B. Companies that acquired a firm with the same approach experience stronger asset growth than their control sample. In contrast, companies that acquire a target with a different competitive

[16] I perform the analysis also with various combinations of industry, year, age, and asset size, and all the results are quantitatively similar.

approach do not materialize such growth. The same conclusion also applies to sales in Appendix C. I conclude that the two samples satisfy the parallel trend assumption necessary for the DiD analysis.

[Insert Figure 5 about Here]

In the DiD analysis, I first estimate the following regression using a panel data set from three years before the bid announcement to three years after the deal announcement separately for the subsample of deals that overlap in the competitive approach and on the subsample of deals without the overlap:

$$Assets_{i,j,t} = \alpha + \beta_1 After_{i,j,t} + \beta_2 After_{i,j,t} * Effective_{i,j} + \eta_{i,j} + \theta_t, \tag{5}$$

where the dependent variable, $Assets_{i,j,t}$, is the acquirer's assets of the deal i, j at time t. The dependent variable in Appendix D is $Sales_{i,j,t}$, the acquirer's sales of the deal i, j. The indicator variable *After* equals one for the postmerger time period and zero otherwise. The indicator variable *Effective* equals one for the treatment deals and zero for the withdrawn deals. The dummy variable *After*Effective* is the interaction term between *After* and *Effective*. I introduce deal and year fixed effects to difference away any time-invariant differences among deals and a common trend affecting deals in both the treatment and control samples.

Table 10 Columns 1 and 2 display coefficient estimates from the OLS regression in Equation 5 using a subsample of deals with and without competitive overlap. The coefficient on the interaction term *After*Effective* is positive and significant at the 1% level for deals with the competitive overlap, while negative and significant at the 5% level for deals without the competitive overlap. Completing a deal between firms with the same competitive approach generates asset growth while buying a target with a different approach results in lower assets.

[Insert Table 10 about Here]

Next, I investigate the heterogeneity in the treatment effect of a merger on postmerger assets, estimating the following equation on the entire sample:

$$
\begin{aligned}
Assets_{i,j,t} = \alpha + \beta_1 After_{i,j,t} + \beta_2 After_{i,j,t} * Effective_{i,j} \\
+\beta_3 SameApproach_{i,j,t-1} * After_{i,j,t} \\
+\beta_4 SameApproach_{i,j,t-1} * After_{i,j,t} * Effective_{i,j} + \eta_{i,j} + \theta_t + \epsilon_{i,j,t},
\end{aligned} \tag{6}
$$

where the dependent variable $Assets_{i,j,t}$, deal and year fixed effects, the indicator variables $After$, $Effective$, and $After * Effective$ are as specified in Equation 5. The dummy variable *SameApproach* equals one for the deals in which the acquirer and the target have the same competitive approach and zero otherwise. The coefficient of interest is β_4 for the interaction term between *SameApproach*, *After*, and *Effective*, which detects the effect on the asset size of acquiring a target with the same competitive approach.

Table 10 Column 3 presents coefficient estimates from the OLS regression in Equation 6. The coefficient on the interaction term *SameApproach**After* is negative and significant at the 5% level. But this decline is reversed for the companies that acquire targets with the same approach; the coefficient on the triple interaction term *SameApproach*After*Effective* is positive and significant at the 1% level. The interaction term is also positive and significant at the 1% level in Appendix D Column 3.[17] The findings establish that the competitive synergies deliver real post-acquisition gains, supporting the paper's predictions.

I assess the robustness of the DiD analysis by conducting a placebo test, where I falsely assume that the companies acquired another company three years before the actual deal materialized. Table 10 Column 4 displays the estimates. The coefficient on the interaction term *SameApproach*After*Effective* is statistically indistinguishable from zero, certifying that the captured asset growth emanates from acquiring the company with the same competitive approach. The findings are the same for sales in Appendix D. The results in this section highlight that companies consider the target firm's competitive approach as an important factor in M&A deals because of the financial and real benefits emerging from the competitive similarity.

[17]Eliminating the acquisition pairs without all seven years (three years before the announcement, the announcement year, and three years after the acquisition) shrinks the sample to 7302 observations, with 5273 observations with the same approach and 2029 observations with a different approach. The results also hold in this smaller sample. The interaction term is positive and significant at the 5% level.

5.5 The underlying mechanism

The hypothesis postulates that companies opt for a target with the same competitive approach because this selection leads to more informed decision-making during important business decisions, such as big investment opportunities or new entrant threats. This section examines the proposed mechanism in two different ways.

First, as taking the available investment and business opportunities is paramount with intense competition, selecting a target firm with the same approach should be more pronounced in highly competitive environments. Namely, if I repeat the analysis from Equation 3 and separate between companies with low competition and companies with high competition, I expect to observe a stronger impact for companies facing more competitive threats.

To separate the sample into low and high competition environments, I use two measures based on processing the text of 10-K annual filings, which acknowledge that each company is surrounded by a unique set of nearby competitors that changes over the years: Hoberg and Phillips (2016) TNIC HHI measure and Hoberg et al. (2014) product fluidity variable. The TNIC HHI measure is the sales-weighted HHI of firms in a firm's industry. The product fluidity variable measures a firm's competitive threats in its product market that captures changes in rival firms' products relative to the firm. I follow Bharath and Hertzel (2019) and define $HighCompetition$ ($HighFluidity$) firms as those with the TNIC HHI (product fluidity) below (above) the sample median.

Table 11 Columns 1 and 2 present the conditional logistic regression results in Equation 3 separately for the subsample of low TNIC HHI industries and the subsample of high TNIC HHI industries. Columns 3 and 4 display the coefficient estimates on the subsamples of the product-fluidity measure. Columns 1 and 3 do not include the control variables, while Columns 2 and 4 also incorporate control variables, as specified in Table 8. The coefficients on $SameApproach$ are all positive and statistically significant at the 1% level, indicating that companies, in general, prefer targets with the same approach. However, positive and highly statistically significant interaction terms $SameApproach * HighCompetition$ and $SameApproach * HighFluidity$ show that the effect is more pronounced with vigorous competition. This result validates the prediction that managers' knowledge and experience are especially vital in intense competition.

[Insert Table 11 about Here]

Second, competitive differences between a target and a bidder in different industries might not be detrimental, as the requirements for success vary between industries (Ramaswamy, 1997). Therefore, I test whether the negative impact of competitive dissimilarity is stronger in the same industry mergers compared to diversifying acquisitions. Table 11 Columns 5 and 6 present the conditional logistic regression results in Equation 3 using the interaction term between the $SameApproach$ and $SameIndustry$ variables. $SameIndustry$ is an indicator variable equal to one if two companies operate in the same industry, as in Chen et al. (2020). Column 5 does not include any control variables, while Column 6 implements the full set of control variables. The coefficient on $SameApproach * SameIndustry$ is positive and statistically significant at the 1% level in both columns, implying that the competitive similarity is more important in the same industry deals, consistent with the predictions. The result substantiates that competitive dissimilarity acts as a constraint to the merged company's market response.

6 Additional evidence

To complete the analysis, this section explores three specific factors that influence M&A decisions: product market, innovation, and culture synergies. Using textual analysis of 10-K product descriptions, Hoberg and Phillips (2010) reveal that firms capitalize on product-market synergies through asset complementarities. They disclose that transactions are more likely between firms that use similar product market language. Also, transaction incidence is higher for firms more broadly similar to all firms in the economy (asset complementarity effect) because those firms have more opportunities for pairings that can generate synergies. It is lower for firms that are more similar to their local rivals (competitive effect), as firms with very near rivals must compete for restructuring opportunities given that a potential partner can view its rivals as substitute partners. Conceptually, product similarity captures a different effect compared to the competitive approach. While product similarity is high for two companies producing the same products (for example, cars), those two companies can be very different in competitive approach (a performance-maximizing and a cost-minimizing producer).

Table 12 Column 1 reestimates the conditional logit regression in Equation 2, where I add the similarity score between the acquirer and the target as a control variable. The coefficient estimates uphold that after including the similarity in the product language, the variable *SameApproach* is still positive and highly statistically significant. I also substantiate that product similarity alters the pairing decisions. Table 12 Column 2 further incorporates broad similarity and product similarity for targets as independent variables. The broad similarity is defined as the average similarity between firm i and all other firms in the sample. Product similarity is the average pairwise similarity between firm i and its ten most similar rivals. The closest rivals are the ten firms with the highest local similarity to i. These measures use the broad and local dictionary, described in Hoberg and Phillips (2010). The two measures do not subsume the effect of the same competitive approach variable. Firms with high local product market competition are less likely to be targets of restructuring transactions, given the existence of multiple substitute target firms. The coefficient on broad similarity for targets turns insignificant after including the control variables and the similarity score between the acquirer and the target. These results conform with the premise of Gimeno and Woo (1996), that companies can be competitively similar with little market overlap but also competitively different with substantial market overlap.

[Insert Table 12 about Here]

The second factor influencing M&A is the technological overlap. Bena and Li (2014) proclaim that its presence between two firms' innovation activities, as captured by the proximity of patent portfolios, shared knowledge bases, and mutual citations of patent portfolios, has a significant effect on the probability of a merger pair formation. They conclude that synergies obtained from combining innovation capabilities are important drivers of acquisitions. From the theoretical perspective, technological proximity should not eliminate the competitive similarity effect for two reasons. First, companies can apply similar competitive approaches even with marginally related technologies (for example, a car and a computer producer). Second, to apply their approaches, many companies do not rely on patents. Table 12 Column 3 mimics the conditional logit regression in Equation 2 with technological proximity as the explanatory variable. Technological proximity measures the closeness of any two firms' innovation activities in the technology space using patent counts in different technology classes. Competitive approach and technological synergies disclose positive and highly statistically significant coefficients. Column 4 displays that the competitive approach significance persists after including both product market and technology variables.

Finally, the section explores whether the main findings are sensitive to the inclusion of the corporate culture variable. I rely on the data from Li et al. (2020), who propose a new proxy for the corporate culture using a semisupervised machine learning technique on earnings calls. They conclude that firms closer in cultural values are more likely to do a deal together. A priori, cultural and competitive similarities indicate different effects. For example, achieving the performance-maximizing approach goals can result from innovations developed by a few very talented people within a company with a strong organizational hierarchy or by teamwork and questioning colleagues' ideas. Thus, I expect that corporate culture does not fully explain the competitive approach variable. I follow the authors and define the cultural distance between two firms as the square root of the sum of squared differences between a firm pair across all five cultural values: innovation, integrity, quality, respect, and teamwork. Table 12 Column 5 presents the conditional logit regression analogous to Equation 2 with the cultural distance as the explanatory variable. The sample size is smaller than the first four columns because the culture variables data begin in 2001. The $SameApproach$ coefficient is positive and statistically significant at the 1% level, in line with the predictions. The coefficient on corporate culture distance is negative and statistically significant at the 1% level, confirming the results of Li et al. (2020). Taken as a whole, this paper uncovers that competitive similarity represents a strong factor affecting M&A deals.

7 Conclusion

This paper provides evidence of the relationship between competitive approaches and firms' investment decisions. It shows that firms consider their own and their target firm's competitive approach in M&A deals. Buying a target company with the same approach yields synergies, visible through financial and real ex-post benefits. The effect is magnified in a highly competitive environment and within the same industry, confirming that managers better understand the business of the same approach companies.

The paper also makes a methodological contribution. I propose a relative proxy to estimate the competitive approach, relying on the life cycle theory and the textual analysis of corporate 10-K financial statements. The novelty is that the phases are not determined by the one-size-fits-all methodology; a company's portfolio of products is compared only with the portfolio of other firms within the same industry. That way, each industry can have companies applying different approaches.

Overall, the paper presents the first cut in understanding the importance of the firm competitive approach in investment decisions. One limitation of this study lies in the sample; it is restricted by the 10-K financial statements, available only for public companies. Future work could propose a method based on the company's products for both private and public firms. Finally, the analysis could also be extended to other related questions, like serial acquirers' approaches and their targets.

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Figure 1: Relation of product life cycle and competitive approach
The figure presents the product life cycle of four car companies: Company A, B, C, and D. The four companies gradually introduce two product innovations: parking sensors and parking cameras. Competitive approaches can be interpreted as the shift in the product life cycle between the companies.

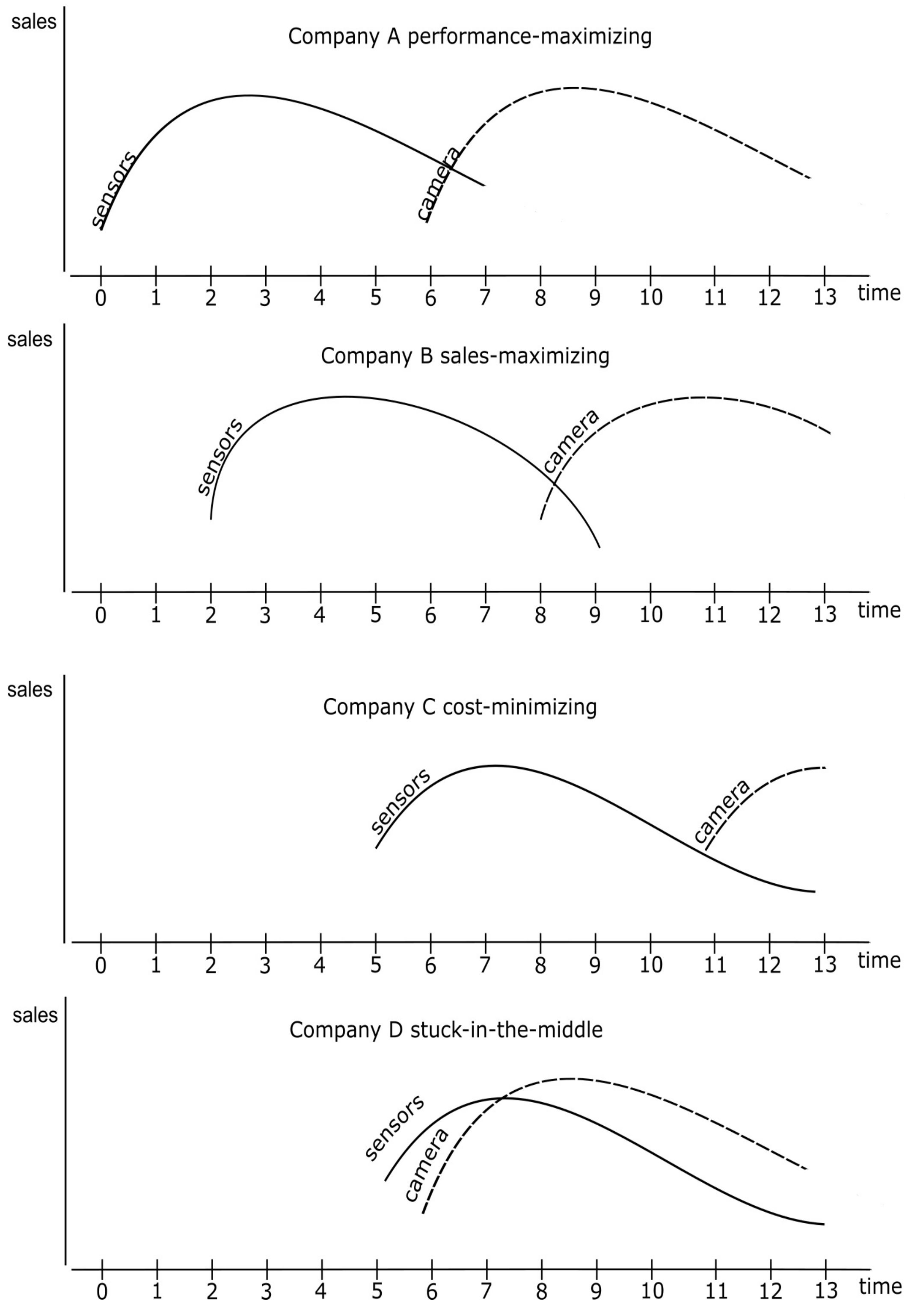


Figure 2: Firm competitive approaches over years
The figure shows the fractions of US firms' competitive approaches between 1994 and 2017. The solid line represents firms applying the performance-maximizing approach, the dashed line shows firms applying the cost-minimizing approach, and the dash-dot and dotted lines stand for the sales-maximizing and stuck-in-the-middle companies, respectively. The sample consists of US public firms with 89,049 firm-year observations. The detailed explanation of the sample is given in Section 3, and the calculation of firm loadings on different approaches is described in Section 4 and Appendix B.

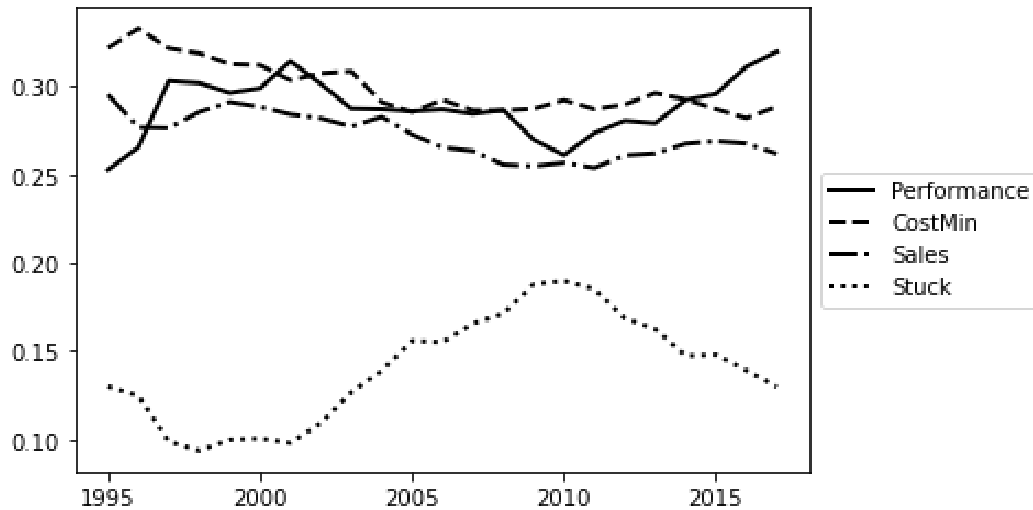


Figure 3: Acquirer competitive approaches over years

The figure shows the fractions of US acquirers' competitive approaches between 1995 and 2017. The solid line represents firms applying the performance-maximizing approach, the dashed line shows firms applying the cost-minimizing approach, and the dash-dot and dotted lines stand for the sales-maximizing and stuck-in-the-middle companies, respectively. The sample consists of 3,104 deals. The detailed explanation of the sample is given in Section 3, and the calculation of firm loadings on different approaches is described in Section 4 and Appendix B.

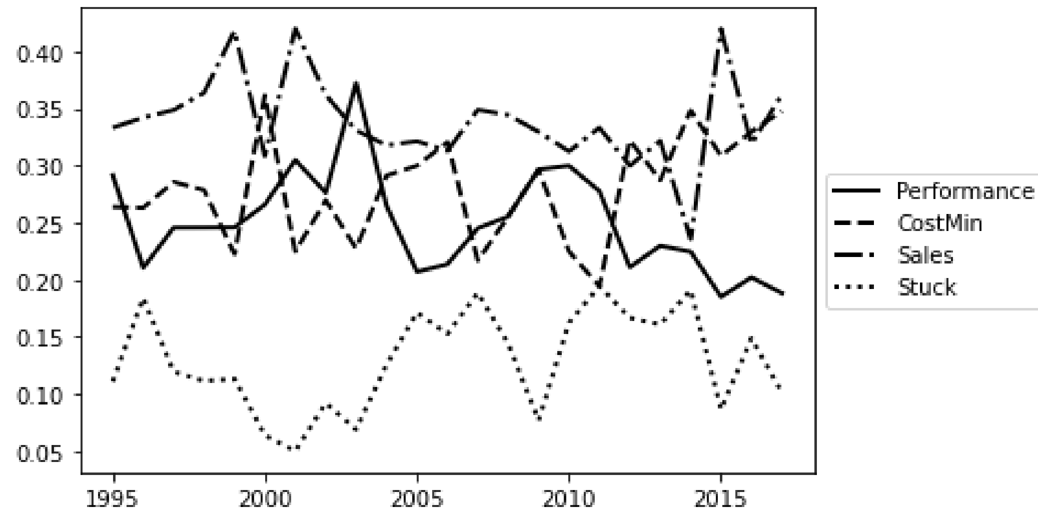


Figure 4: Target firms' competitive approaches over years
The figure shows the fractions of US target firms' competitive approaches between 1995 and 2017. The solid line represents firms applying the performance-maximizing approach, the dashed line shows firms applying the cost-minimizing approach, and the dash-dot and dotted lines stand for the sales-maximizing and stuck-in-the-middle companies, respectively. The sample consists of 3,104 deals. The detailed explanation of the sample is given in Section 3, and the calculation of firm loadings on different approaches is described in Section 4 and Appendix B.

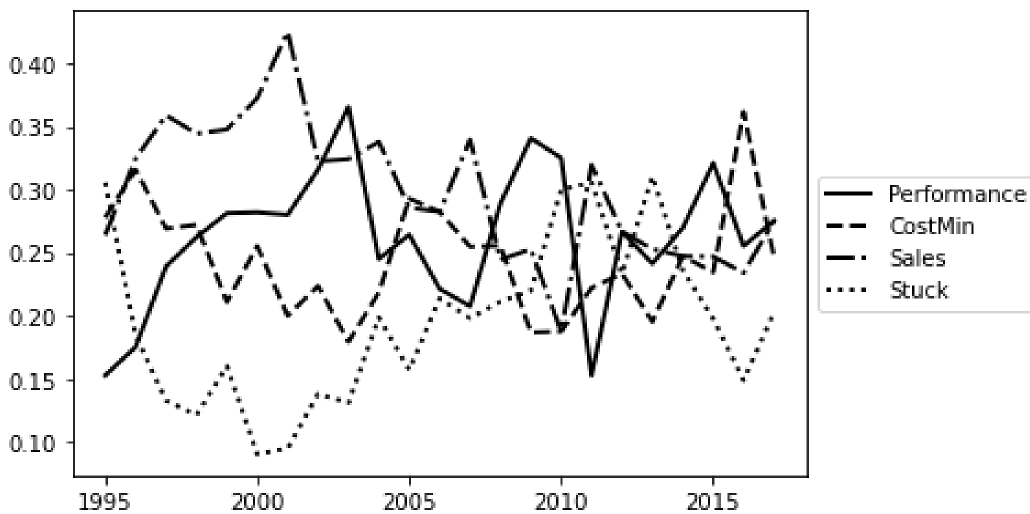


Figure 5: Asset size of acquirers and companies that withdrew their bid
The figure plots the average asset size of the acquirers and companies that announced a deal but withdrew their bid. I use panel data running from three years before the bid announcement to three years after the announcement. Panel A consists of the deals in which the acquirer and the target apply the same competitive approach, while Panel B displays the deals with the acquirer and the target with different approaches. The gray area on the graph marks the announcement year.

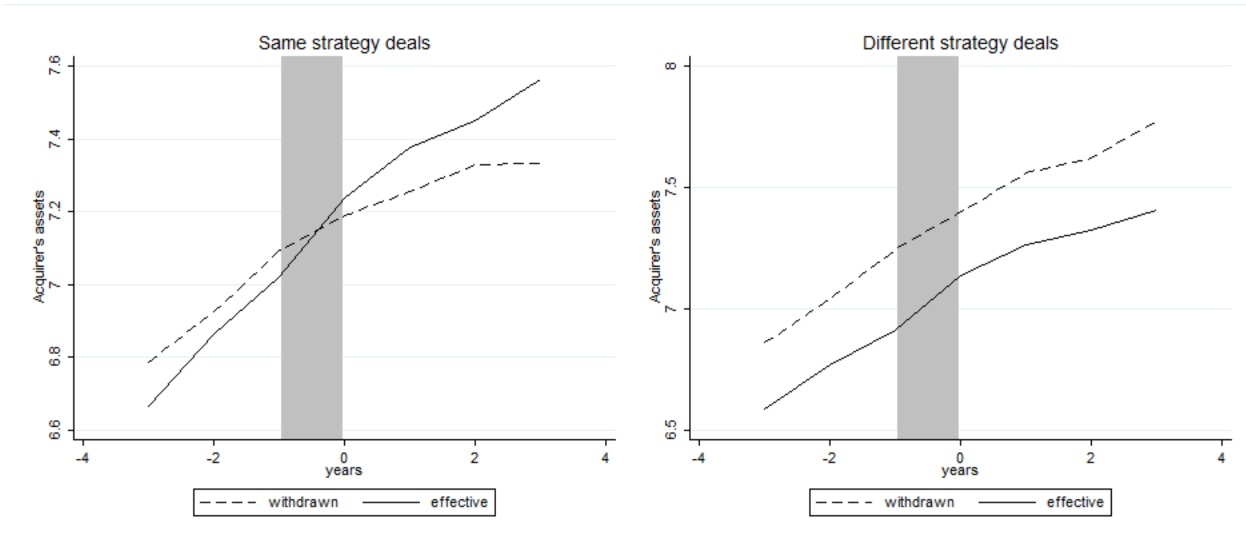


Table 1: Public corporate acquisitions over time, 1995-2017
The table reports the distribution of M&A sample of US public acquirers and targets together with their subsidiaries, announced and completed during the period 1995-2017. It shows the total number of M&A in the sample during a year, the ratio of public and subsidiary targets, the fraction of deals payed only with cash, only with stock, and other type of payment deals. The total number of M&A deals in the sample is 3,104. Sample criteria are described in detail in Section 3.

Year	Number	Public	Subsidiary	CashDeal	StockDeal	MixDeal
1995	72	0.24	0.76	0.17	0.14	0.69
1996	114	0.29	0.71	0.32	0.15	0.54
1997	301	0.40	0.60	0.34	0.18	0.49
1998	305	0.40	0.60	0.30	0.21	0.48
1999	256	0.48	0.52	0.30	0.21	0.48
2000	188	0.41	0.59	0.33	0.16	0.51
2001	200	0.42	0.57	0.32	0.16	0.52
2002	152	0.27	0.73	0.40	0.11	0.49
2003	145	0.39	0.61	0.36	0.10	0.54
2004	151	0.36	0.64	0.42	0.10	0.48
2005	140	0.42	0.58	0.48	0.08	0.44
2006	131	0.34	0.66	0.53	0.06	0.40
2007	106	0.42	0.58	0.62	0.01	0.37
2008	90	0.40	0.60	0.52	0.03	0.44
2009	91	0.40	0.60	0.46	0.05	0.48
2010	80	0.45	0.55	0.57	0.06	0.36
2011	72	0.29	0.71	0.44	0.03	0.53
2012	90	0.33	0.67	0.52	0.04	0.43
2013	87	0.36	0.64	0.51	0.06	0.44
2014	89	0.37	0.63	0.34	0.10	0.56
2015	81	0.54	0.46	0.43	0.05	0.52
2016	94	0.47	0.53	0.57	0.05	0.37
2017	69	0.43	0.57	0.42	0.09	0.49
Total	3104	0.39	0.61	0.40	0.12	0.48

Table 2: Summary statistics

The table reports summary statistics for the acquirers and the target firms. The sample consists of 3,104 US public deals, announced and completed during the period 1995-2017. Sample criteria are described in detail in Section 3. Definitions of the variables are provided in Section 3.

Variable	Mean	Std	25%	50%	75%
			Acquirers		
Assets	6.98	2.00	5.60	6.99	8.42
Age	11.97	6.01	8.00	10.00	16.00
Debt	0.20	0.20	0.03	0.17	0.31
R&D	0.12	0.86	0.00	0.01	0.08
EBITDA	0.12	0.15	0.09	0.14	0.19
MB	2.30	2.30	1.32	1.73	2.51
			Targets		
Assets	6.73	2.27	4.98	6.65	8.53
Age	11.36	5.79	7.00	10.00	15.00
Debt	0.20	0.21	0.02	0.17	0.31
R&D	0.20	1.23	0.00	0.02	0.10
EBITDA	0.07	0.23	0.05	0.11	0.17
MB	2.01	1.92	1.18	1.54	2.21

Table 3: Average firm characteristics by competitive approach group

The table reports average age, asset growth, market-to-book ratio, the ratio of research and development over sales, long term debt over assets, number of patents (#Pat), the ratio of patent value over assets ($Pat), and the average of the four product life-cycle phases (Life1-Life4). The sample consists of 89,069 firm-year observations between 1995 and 2017. Number of patents and value of patents are from Kogan et al (2017). The detailed explanation of the firm approach and product life-cycle measures is given in Section 4. Definitions of the variables are provided in Section 3.

Firm LC	Age	Growth	MB	R&D	Debt	$Pat	#Pat	Life1	Life2	Life3	Life4
Performance-max	9.70	1.25	3.21	0.93	0.15	0.06	6.60	0.42	0.32	0.22	0.04
Sales-max	10.65	1.22	2.45	0.14	0.22	0.01	8.47	0.22	0.34	0.39	0.04
CostMin	11.04	1.17	2.29	0.18	0.25	0.01	4.19	0.17	0.58	0.21	0.04
Stuck	13.37	1.13	2.00	0.15	0.23	0.01	6.55	0.16	0.36	0.20	0.27

Table 4: Transition matrix of firm life-cycle in one year horizon.
The table reports the transition matrix of firm approaches for US public firms during the period 1994-2017. The detailed explanation of the firm approach is given in Section 4.

	Approach in the following year			
Approach	Performance-max	Sales-max	CostMin	Stuck
Performance-max	83%	6%	8%	3%
Sales-max	7%	8%	81%	4%
CostMin	5%	84%	6%	4%
Stuck	4%	8%	6%	81%

Table 5: Likelihood of becoming a target or an acquirer

The table reports the coefficient estimates of the conditional logistic regression, where the dependent variable is a dummy variable equal to 1, if a firm becomes an acquirer (target) in a given year and zero otherwise. Cost-minimizing group serves as the reference category in all the columns. The independent variables are measured at the fiscal year-end immediately prior to acquisition announcement date. Definitions of the variables are provided in Section 3. The detailed explanation for the control sample is given in Section 5.3. Control sample in Columns 1, 2, 4, and 5 is based on firm size. Control sample in Columns 3 and 6 is based on firm size and age. Standard errors clustered at the deal level are reported in the parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Acquirer	(2) Acquirer	(3) Acquirer	(4) Target	(5) Target	(6) Target
Performance-max	0.961***	0.570***	0.676***	1.158***	0.681***	0.963***
	(0.059)	(0.076)	(0.060)	(0.061)	(0.074)	(0.064)
Sale-max	0.222***	0.117**	0.172***	0.262***	0.278***	0.256***
	(0.052)	(0.055)	(0.053)	(0.054)	(0.059)	(0.056)
Stuck	-0.147**	-0.136*	-0.151**	0.334***	0.349***	0.296***
	(0.071)	(0.071)	(0.071)	(0.067)	(0.068)	(0.067)
Age		-0.103***			-0.061***	
		(0.006)			(0.005)	
MB		0.108***	-0.009***		0.093***	-0.045***
		(0.014)	(0.002)		(0.022)	(0.013)
EBITDA		1.220***	1.433***		-3.529***	-0.178***
		(0.171)	(0.196)		(0.380)	(0.062)
Debt		-0.664***	-0.794***		-0.346**	-0.663***
		(0.155)	(0.156)		(0.169)	(0.171)
R&D		1.820***	0.211***		2.948***	0.159***
		(0.577)	(0.052)		(0.405)	(0.048)
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.03	0.09	0.04	0.04	0.12	0.04
Observations	18620	18620	18620	18621	18621	18621

Table 6: Acquirer-target approach pairs

The table shows the number of acquirer-target matched approach pairs. The calculation of firm competitive approach is provided in Section 4. The explanation of the sample is given in Section 3.

	Targets' approach				
Acquirers' approach	Performance-max	CostMin	Sales-max	Stuck	Total
Performance-max	374	110	205	98	787
CostMin	141	348	212	161	862
Sales-max	238	203	474	162	1,077
Stuck	69	100	94	115	378
Total	822	761	985	536	3,104

Table 7: Example deals of mergers and acquisitions in each acquirer-target approach group
The detailed explanation of the competitive strategy measure is given in Section 4.

Acquiror approach	Target approach	Acquirer name	Target name	Year announced	Transaction value
Performance-max	Performance-max	Tesla motors	Solarcity	2016	$2.6bil
Performance-max	CostMin	Boston Scientific	Celsion	2007	$60mil
Performance-max	Sales-max	Ebay	Paypal	2002	$1.4bil
Performance-max	Stuck	Pfizer	Encysive Pharm	2008	$186mil
CostMin	Performance-max	Johnson&Johnson	Innotech	1997	$135mil
CostMin	CostMin	Delta Airlines	Northwest Airlines	2008	$2.9bil
CostMin	Sales-max	Alaska Air	Virgin America	2016	$4.2bil
CostMin	Stuck	New York Times	About.Com	2005	$410mil
Sales-max	Performance-max	Coca-Cola	Monster Beverage	2014	$2.1bil
Sales-max	CostMin	3M Co	Cogent Systems	2010	$932mil
Sales-max	Sales-max	Amazon	Whole foods	2017	$13.6bil
Sales-max	Stuck	AT&T	Dobson Commun	2007	$5.4bil
Stuck	Performance-max	3M Co	Robinson Nugent	2000	$123mil
Stuck	CostMin	Chiquita	Stokely	1997	$43mil
Stuck	Sales-max	Pepsi	Quaker Oats	2000	$14.4bil
Stuck	Stuck	Occidental Petroleum	Vintage Petroleum	2005	$3.6bil

Table 8: Acquirer-target firm pairing

The table shows the coefficient estimates from conditional logit model, where the dependent variable is a dummy variable equal to one if a given company pair is the true acquirer-target pair in a given year and zero otherwise. For each deal, there is one observation for the acquirer (target firm), and up to five observations of the control acquirers (target firms). The control sample is based on the propensity-matching score within the same industry and the same year. The first two columns match additionally on assets, while the last column matched additionally on assets and age. The calculation of firm strategy is given in Section 4. Definitions of the variables are provided in Section 3. Standard errors clustered at the deal level are given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) RealPair	(2) RealPair	(3) RealPair
SameApproach	0.739***	0.705***	0.738***
	(0.043)	(0.043)	(0.042)
Age_acq		-0.080***	
		(0.005)	
MB_acq		0.108***	-0.003**
		(0.011)	(0.002)
EBITDA_acq		1.064***	0.959***
		(0.149)	(0.129)
Debt_acq		-0.752***	-0.760***
		(0.124)	(0.105)
R&D_acq		1.617**	0.160***
		(0.632)	(0.031)
Age_tar		-0.052***	
		(0.004)	
MB_tar		0.117***	-0.020***
		(0.021)	(0.003)
EBITDA_tar		-2.298***	-0.079***
		(0.376)	(0.024)
Debt_tar		-0.480***	-0.701***
		(0.123)	(0.112)
R&D_tar		2.763***	0.145***
		(0.404)	(0.028)
Pseudo R^2	0.02	0.08	0.03
Observations	34137	34137	34137

Table 9: Combined announcement returns

This table reports OLS regression results for the combined announcement returns, CAR (-1,1), measured using Carhart four-factor model returns. Combined returns are weighted by the market capitalization of acquirers and targets ten days before the announcement day. The detailed explanation of the competitive strategy measure is given in Section 4. Definitions of the control variables are provided in Section 5.4. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) CombinedReturn	(2) CombinedReturn
SameApproach	0.725**	0.869***
	(0.271)	(0.286)
RelativeSize		0.726*
		(0.418)
CashDeal		1.745***
		(0.463)
StockDeal		-2.515***
		(0.654)
DiffInd		-0.994**
		(0.395)
Subsidiary		-2.360***
		(0.426)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Control variables	No	Yes
R^2	0.02	0.09
Observations	3104	2493

Table 10: Long-term assets of acquirers

The table presents the coefficient estimates of difference-in-differences regression, where the dependent variable is the logarithm of acquirer's asset size. Column 1 presents the coefficient estimates on a subsample of same strategy deals, Column 2 shows the coefficient estimates on a subsample of different strategy deals, Column 3 includes all deals, while Column 4 is the placebo test, where it is falsely assumed that the acquirers acquired a company three years before the actual acquisition on the entire sample of deals. The dependent variable is the acquirer's assets of the deal m. The indicator variable *After* equals one for the postmerger time period, and zero otherwise. The indicator variable *Effective* equals one for the treatment deals and zero for the withdrawn deals. The indicator variable *SameApproach* equals one for the deal where the acquirer and target overlap in the competitive strategy, and zero otherwise. The interactions terms between different variables are marked with $\times$. The selection of withdrawn acquisitions is described in Section 5.4. All columns include deal and year fixed effects. Robust standard errors are reported in the parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Assets	(2) Assets	(3) Assets	(4) FalsificationTest
After	0.323*	-0.320	0.394**	-0.008
	(0.182)	(0.315)	(0.175)	(0.204)
After × Effective	0.128***	-0.207**	-0.213**	-0.242**
	(0.049)	(0.085)	(0.085)	(0.095)
SameApproach × After			-0.208**	-0.010
			(0.082)	(0.094)
SameApproach × After × Effective			0.340***	0.153
			(0.098)	(0.108)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	6.713***	6.728***	6.717***	6.836***
	(0.040)	(0.075)	(0.035)	(0.042)
R^2	0.65	0.62	0.64	0.60
Observations	7119	2526	9645	7718

Table 11: Economic mechanism testing

The table presents the coefficient estimates from conditional logit model, where the independent variable is an indicator variable equal to one if a given company pair is the true acquirer-target pair in a given year, and zero otherwise. For each deal, there is one observation for the acquirer (target firm) and up to five observations of the control acquirers (target firms). The control sample is based on the propensity matching score within the same industry and the same year. Columns 1 and 2 show the coefficient estimates of the HHI variable, Columns 3 and 4 show the coefficient estimates of the product fluidity variable, and Columns 5 and 6 estimate the difference between same industry acquisitions and different industry acquisitions. Standard errors clustered at the deal level are given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) RealPair TNIC-HHI	(2) RealPair TNIC-HHI	(3) RealPair Fluidity	(4) RealPair Fluidity	(5) RealPair Industry	(6) RealPair Industry
SameApproach	0.581***	0.589***	0.475***	0.497***	0.294***	0.368***
	(0.061)	(0.071)	(0.060)	(0.068)	(0.079)	(0.096)
HighCompetition	0.040	0.168***				
	(0.044)	(0.064)				
SameApproach × HighCompetition	0.232***	0.179*				
	(0.084)	(0.096)				
HighFluidity			-0.076*	-0.058		
			(0.045)	(0.064)		
SameApproach × HighFluidity			0.441***	0.364***		
			(0.084)	(0.096)		
SameApproach × SameIndustry					0.574***	0.438***
					(0.094)	(0.110)
Control variables	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.02	0.30	0.02	0.30	0.02	0.30
Observations	29233	29233	29233	29233	29233	29233

Table 12: Firm pairs with synergy variables
The table presents the coefficient estimates from conditional logit model, where the dependent variable in an indicator variable equal to one if a given company pair is the true acquirer-target pair in a given year and zero otherwise. For each deal, there is one observations for the acquirer (target firm) and up to five observations of the control acquirers (target firms). The control sample is based on the propensity matching score within the same industry and the same year. $TwoCompScore$ is the similarity score between the companies. $BroadSimilarity_{acq}$ and $BroadSimilarity_{tar}$ are the broad similarity of acquirers and targets. $ProductSimilarity_{acq}$ and $ProductSimilarity_{tar}$ are the product similarities of acquirers and targets. $TechProx$ is the technological proximity of the given firm pair. $CulturalDis$ is the cultural distance between the firm-pair. Definitions of the control variables are provided in Section 5.4. Standard errors clustered at the deal level are given in the parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) RealPair	(2) RealPair	(3) RealPair	(4) RealPair	(5) RealPair
SameApproach	0.643***	0.668***	0.649***	0.619***	0.638***
	(0.047)	(0.048)	(0.044)	(0.048)	(0.083)
TwoCompScore	0.153***	0.198***		0.194***	
	(0.005)	(0.006)		(0.006)	
BroadSimilarity_acq		0.078*		0.092**	
		(0.043)		(0.044)	
ProductSimilarity_acq		0.005		0.005	
		(0.006)		(0.006)	
BroadSimilarity_tar		-0.069		-0.060	
		(0.058)		(0.060)	
ProductSimilarity_tar		-0.097***		-0.098***	
		(0.007)		(0.007)	
TechProx			2.917***	2.335***	
			(0.156)	(0.156)	
CulturalDis					-0.133***
					(0.021)
Control variables	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.34	0.37	0.26	0.39	0.38
Observations	34137	34137	34137	34137	9661

A Appendix

Relation between approach and life-cycle

The table shows the coefficient estimates from logit model, where the dependent variable $Perf$ in the first four columns is a dummy variable equal to one if a company belongs to the performance-maximizing group in a given year. The dependent variable in Columns 5 to 8 is $CostMin$, a dummy variable equal to one if a company belongs to the cost-minimizing group in a given year, and zero otherwise. Columns 9 to 12 focus on $Sales$, a dummy variable equal to one if a company belongs to the sales-maximizing group in a given year, and zero otherwise. The dependent variable in the last four columns is $Stuck$, a dummy variable equal to one if a company belongs to the stuck-in-the-middle group in a given year, and zero otherwise. The calculation of firm strategy is given in Section 4. Definitions of the variables are provided in Section 3. Standard errors clustered at the deal level are given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Perf	Perf	Perf	Perf	CostMin	CostMin	CostMin	CostMin	Sales	Sales	Sales	Sales	Stuck	Stuck	Stuck	Stuck
Age	0.000			-0.015***	0.038***			0.050***	0.022***			0.028***	0.086***			0.106***
	(0.001)			(0.001)	(0.001)			(0.001)	(0.001)			(0.001)	(0.001)			(0.002)
Assets	-0.000***			-0.000***	0.000***			0.000***	0.000***			0.000***	0.000***			0.000***
	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)
ReAt	0.000			0.000	0.000***			0.000***	0.000***			0.000*	0.000			0.000
	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)
Constant	-1.323***	-1.231***	-1.458***	-2.718***	-1.746***	-1.361***	-1.247***	-2.771***	-1.721***	-1.482***	-1.366***	-2.725***	-3.247***	-2.291***	-2.396***	-3.882***
	(0.013)	(0.037)	(0.109)	(0.136)	(0.014)	(0.038)	(0.102)	(0.132)	(0.014)	(0.040)	(0.106)	(0.135)	(0.021)	(0.054)	(0.154)	(0.178)
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
PseudoR^2	0.002	0.02	0.008	0.028	0.011	0.015	0.005	0.031	0.008	0.016	0.002	0.024	0.049	0.099	0.005	0.062

B Appendix

Following Hoberg and Maksimovic (2022), I measure the firm loadings on life-cycle stages based on all paragraphs in 10-K that contain at least one word from each of the following two lists.

Life1 List A: product OR products OR service OR services
Life1 List B: development OR launch OR launches OR introduce OR introduction OR introductions OR new OR introducing OR innovation OR innovations OR expansion OR expanding OR expand

Life2 List A: cost OR costs OR expense OR expenses
Life2 List B: labor OR employee OR employees OR wage OR wages OR salary OR salaries OR inventories OR inventory OR warehouse OR warehouses OR warehousing OR transportation OR shipping OR freight OR materials OR overhead OR administrative OR manufacturing OR manufacture OR production OR equipment OR facilities OR

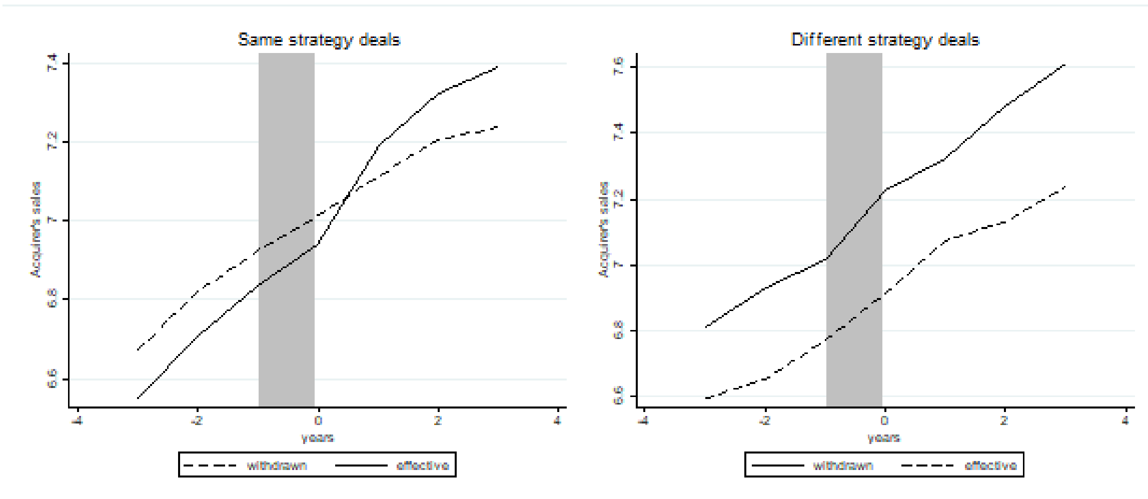
Life4 List A: product OR products OR service OR services OR inventory OR inventories OR operation OR operations
Life4 List B: obsolete OR obsolescence OR discontinued OR discontinue OR discontinuance OR discontinuation OR discontinues OR discontinuing

To measure the loading on Life3, I require three word lists, instead of two used in the other LC. A firm's 10-K must contain at least one word from List A and List B, and must not contain any words from the List C.

Life3 List A: product OR products OR service OR services
Life3 List B: line OR lines OR offerings OR mix OR existing OR portfolio OR current OR categories OR category OR continue OR group OR groups OR customer OR customers OR core OR consists OR continues OR provide OR providing OR provided OR providers OR includes OR continued OR consist
Life3 List C(exclusions): development OR launch OR launches OR introduce OR introduction OR introductions OR new OR introducing OR innovation OR innovations OR expansion OR expanding OR expand OR future OR obsolete OR obsolescence OR discontinued OR discontinue OR discontinuance OR discontinuation OR discontinues OR discontinuing OR cost OR costs OR expense OR expenses

C Appendix

Sales of acquirers and companies that withdrew their bid in the same competitive approach deals and different approach deals
The figure plots the average sale size of the acquirers and companies that announced a deal but withdrew their bid. Panel data runs from three years before the bid announcement to three years after the announcement. Panel A consists of the deal in which the acquirer and the target apply the same competitive approach, while Panel B displays the deals with non-overlapping approaches. The gray area on the graph marks the announcement year.



D Appendix

Long-term sales of acquirers

The table presents the coefficient estimates of difference-in-differences regression, where the dependent variable is the logarithm of acquirer's sales of the deal m. Column 1 presents the coefficient estimates on a subsample of same approach deals, Column 2 on a subsample of different approach deals, Column 3 includes all deals, while Column 4 is the placebo test, where it is falsely assumed that the acquirers acquired a company three years before the actual acquisition on the entire sample of deals. The indicator variable *After* equals one for the postmerger time period, and zero otherwise. The indicator variable *Effective* equals one for the treatment deals and zero for the withdrawn deals. The indicator variable *SameApproach* equals one for the deal where the firms overlap in the competitive approach, and zero otherwise. The interactions terms between different variables are marked with ×. All columns include deal and year fixed effects. Robust standard errors are reported in the parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Sales	Sales	Sales	FalsificationTest
After	0.148	0.601**	0.366**	-0.124
	(0.205)	(0.266)	(0.187)	(0.221)
After × Effective	0.052	-0.250***	-0.248***	-0.141
	(0.049)	(0.083)	(0.083)	(0.101)
SameApproach × After			-0.172**	0.113
			(0.081)	(0.095)
SameApproach × After × Effective			0.301***	-0.082
			(0.096)	(0.114)
Constant	6.601***	6.694***	6.625***	6.729***
	(0.042)	(0.074)	(0.036)	(0.042)
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.666	0.604	0.650	0.625
Observations	7,066	2,516	9,582	7,677