Strategic similarity in mergers and acquisitions

by

Tina Oreski*

*Swiss Finance Institute and USI Lugano (Universita della Svizzera Italiana), Via Buffi 13, 6900 Lugano, Switzerland, email:tina.oreski@usi.ch. I would like to thank Laurent Fresard for his advice and many helpful discussions. I also thank Emanuele Bettinazzi, Bruno Biais (discussant), Francesco D'Acunto, Zoran Filipovic, Vyacheslav Fos, Zongbo Huang (discussant), Gael Imad'Eddine (discussant), Gordon Phillips, Luc Renneboog, Mirela Sandulescu, Norman Schurhoff (discussant), Davide Tedeschini, Yuxin Wu (Cedric), and seminar participants at USI Lugano, SFI research days 2019, Boston College, 17th Corporate Finance Day, AFA 2021 poster session, Nova Ph.D. Finance event 2021, SWFA 2021, SGF 2021, AFFI 2021 for their comments.

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Abstract

Using textual analysis and product life cycle to proxy for a company's competitive strategy, this paper empirically examines the strategic similarity hypothesis. The findings show that mergers and acquisitions deals are more likely between companies implementing the same strategy. Moreover, same strategy deals yield higher combined announcement returns, asset and sales growth. The effect is more pronounced in a highly competitive environment and within an industry, confirming that strategic misalignment acts as a constraint to the merged company's optimal response to investment opportunities and market threats. Overall, the results reveal that competitive strategy constitutes an important determinant of firms' investment decisions.

Keywords: mergers and acquisitions, competitive strategy, synergies, firm life cycle, textual analysis

1 Introduction

Competitive strategy determines the way companies allocate their scarce resources to achieve competitive advantage and maximize profits and firm value (Caves, 1980). It strongly relates to the types of products or services a firm offers on the market (Utterback and Abernathy, 1975). The literature categorizes companies into four competitive strategies. Performance-maximizing firms compete based on innovative products and services; cost-minimizing companies emphasize efficiency in cost production and compete based on low product prices; sales-maximizing companies rely on greater diffusion of their products or services and stable relationship with their customers; stuck-in-the-middle companies do not manage to consistently apply any of the first three strategies and they end up with more obsolete products.[1] Hence, competitive strategy has direct implications for firms' investment decisions. Yet, financial economists have largely ignored this relation. This paper eliminates the gap by empirically examining whether firms' competitive strategies affect one of their biggest investment decisions: mergers and acquisitions (M&A).

The finance literature has shown that the overlap in the product, technology, human capital, and culture dimension between the acquirer and the target firm are important drivers of M&A transaction incidence and performance (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 strategies and their similarity. Consequently, to begin the analysis, I resort to the strategic management and industrial organization literature.

Caves and Porter (1977) and Prahalad and Bettis (1986) models predict that companies with the same strategy allocate their scarce resources and respond to entrant threats similarly. Building on this framework, the strategic similarity hypothesis postulates that deals where the acquiring and target firm implement the same strategy (henceforth, same strategy deals) outperform other deals (Ramaswamy, 1997). The mechanism underscores that the misalignment between the target and bidder strategic approaches causes decision delays on new investment opportunities and market threats (Swaminathan et al., 2008), which acts as a constraint to the merged company's optimal response and diminishes potential synergies. The strategic management and industrial organization

[1] The first three categories closely follow the classification of Utterback and Abernathy (1975). Following Kim and Lim (1988) and Porter (1980) or Miles and Snow (1978), I define an additional group, stuck-in-the-middle companies, which do not manage to consistently apply any of the first three remaining strategies and they end up with more obsolete products.

literature have investigated the hypothesis with survey evidence or focusing only on the banking industry, which hampered the researchers to generalize the findings.[2] In this paper, I propose a method to estimate companies' competitive strategies applicable to a large sample of public companies and I test the hypothesis on US public M&A across various industries.

To validate the hypothesis, I need a proxy for the firms' competitive strategies. Utterback and Abernathy (1975) model the change in competitive strategies over firms' product life cycle. Thus, I employ product life cycle as the proxy for firm competitive strategy.[3] Since a company can have multiple products in different life cycle stages, I follow Hoberg and Maksimovic (2019) and exploit the textual analysis of 10-K financial statements to map 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 pertaining to a particular stage. However, the emphasis companies put on products in different life cycles (their innovations, rate of change, durability, minimization of costs, and relations with suppliers and customers) varies significantly across industries. Therefore, I include an additional step to measure firm competitive strategy. I compare the product life cycle of a firm with its most similar firms and detect the product life cycle that obtains the highest ranking within the matching industry. This step embeds the proxy's relative aspect: a firm's strategy 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 strategies.

In line with the economic theory, companies oriented towards performance-maximizing strategy 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 strategies 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' strategic orientation. This result suggests that competitive strategy carries different information not absorbed by the life-cycle proxies, which can bolster our understanding of the companies' investment decisions.

With the new proxy for companies' strategies 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

[2] see Ramaswamy (1997); Altunbaş and Marqués (2008); Stimpert and Duhaime (1997); Bauer and Matzler (2014)
[3] The relation dates back to Wasson (1974), Hofer (1975), Rink and Swan (1979).

spread through all the strategic groups. Nonetheless, performance-maximizing and stuck-in-the-middle companies realize the highest probability of becoming targets, while companies in the sales-maximizing and performance-maximizing group are associated with the highest likelihood of becoming acquirers. The result highlights that companies do not exhaust all their internal investment opportunities before acquiring other companies, but they continuously weigh all the viable alternatives. Additionally, 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 strategic traits are twice as large as the odds for companies that belong to dissimilar strategies. This acquirer-target pair pattern reveals that firms anticipate the obstacles stemming from a partner with a different competitive posture and opt for a one with the same strategy, which aligns post-acquisition objectives and expedites decision-making. Third, deals with strategy overlap earn, on average, 87 basis points higher combined announcement returns, and the acquirer's assets and sales increase significantly after the acquisition compared with the companies that bought a target with a different strategy. The analysis supports that acquirers buying strategically related target firms outperform other acquirers.

Next, I test the theory's driving force, namely, that the strategic misalignment induces a company's suboptimal response to investment and business opportunities. Intense competition demands a company's swift response due to the predatory risk.[4] Hence, eliminating the potential difficulties and emphasizing prompt decision-making should be particularly relevant in a high-competition environment. 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 in the same strategy. Moreover, the theory assumes that strategic 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 strategic dissimilarity is more pronounced in the same or different industry acquisitions. The results provide strong support for the claim. These findings corroborate the strategic similarity prediction that the same strategic orientation reduces difficulties in reaching a consensus between the acquirer and the target in critical business decisions, resulting in better deal performance.

[4]see Makadok (1998); Christie et al. (2003); Haushalter et al. (2007); Valta (2012)

I complement the analysis with several robustness tests. I explicitly consider whether the results are driven by the traditional life cycle proxies and variables that have been 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 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 strategies 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 the 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. Bettinazzi et al. (2020) point out that target selection is skewed towards firms with similar ownership. Chen et al. (2020b) emphasize the impact of search efficiency on merger process and outcomes. I document that synergies arising from strategic similarity constitute a strong determinant of public M&A decisions.

The paper also adds to the literature on the importance of strategy and life cycle in financial decisions. O'Brien (2003) focuses on how one type of competitive strategy, the industry innovator, impacts the capital structure. The paper maintains that the appropriate proxy for the strategic importance of a firm's innovativeness is the relative intensity of investment in R&D (relative to other firms in the same industry). Arikan and Stulz (2016) advocate that the acquisition rate follows a U-shape pattern over firms' life-stage and that younger firms make more related and diversifying acquisitions than mature firms. DeAngelo et al. (2010) establish that the firm's life cycle influences the decision to conduct a seasoned equity offering. I find that companies' acquisition decisions depend on their but also on their target firms' competitive strategies.

Finally, my paper enriches the fast-growing research in finance that employs textual analysis for hypothesis testing. 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 (2019) 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. (2020a) 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 new measure based on textual analysis of 10-K financial statements, which offers evidence on the importance of the strategic similarity in M&A.

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:

1. The acquirers and the targets are publicly listed US firms.
2. The deal is completed.
3. The acquirer holds less than 50% of the target before the transaction and more than 50% after the transaction.

4. 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.
5. Date effective, percentage of shares owned after the transaction, and percentage of shares acquired are nonmissing.
6. A 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, 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 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 strategy measure

To find an attribute representing the firm's strategy applicable to the 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 emphasis on product variety and later emphasis on product standardization and costs, and that competitive strategy strongly relates to this development. Ergo, I apply the product life cycle as a proxy for the firm's competitive strategy.

To measure firm's product life cycle, I build on a recent finance literature approach that relies on textual analysis of firms' financial statements (Hoberg and Maksimovic, 2019; Chen et al., 2020a). 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 (2019), 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 A describes the procedure in detail. I deviate from the exact Hoberg and Maksimovic (2019) 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. I normalize the product life cycle exposure vector with the four individual paragraph counts by dividing each number by the total paragraph counts.

Consequently, each company maps to a four-element vector 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 firm competitive strategy, I calculate for each company-year the percentile ranking of every product life cycle within the industry[6] in a three-year period. I set the product-phase with less than 15% to zero percentile

[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]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).

to avoid classifying companies into stages that do not represent a relevant part of the portfolio of products. The product life cycle with the highest ranking denotes the company's competitive strategy.[7] That way, a company's strategy is determined with respect to 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 strategy if the highest percentile accompanies the second product phase. I sort a firm as a sales-maximizing or a stuck-in-the-middle company whenever the firm's dominant product life cycle percentile is in the third or the fourth phase, respectively. Thereby, the competitive strategy measure indicates the company's highest product life cycle percentile within its industry in a three-year period, and it designates companies to performance-maximizing, cost-minimizing, sales-maximizing, or stuck-in-the-middle group.[8]

Performance-maximizing strategy 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 the customers and suppliers. The emphasis is placed on expanding sales and gaining market share. As the product life cycle evolves, companies focus on process innovations and efficiency in manufacturing and distribution of products to reach low product prices, at which point they apply the cost-minimizing strategy. Finally, stuck-in-the-middle companies struggle to consistently apply any of the first three strategies and they end up with more obsolete products.

Table 3 summarizes the average firms' characteristics in each strategy group. In line with the economic theory, 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.[9] Consistent with the findings of Kogan et al. (2017) that large firms tend to file more

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

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

[9] 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

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 firm strategy 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 stack more on minimizing the costs in absolute terms.

[Insert Table 3 about Here]

4.1 Dynamics of competitive strategies

Figure 1 depicts the ratio of firm strategies 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.[10] 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 1 about Here]

Table 4 discloses the other type of dynamics: the mobility between the strategies in a one-year horizon.[11] It outlines that firms primarily remain in the same strategy group. Still, the lack of zero loadings in all the transition matrices confirms that companies may progress from the current to any of the three remaining strategies. One of the leading examples of the strategy changes is Apple

[10] 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).

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

in 1995. Twenty years after the 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 extreme changes within one year, the movement from the performance-maximizing to the stuck-in-the-middle strategy, and vice versa 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.

4.2 Comparison with life cycle proxies

In this section, I compare the strategy proxy with the life cycle proxies adopted in the finance literature so far: age by Arikan and Stulz (2016), dividend increases by Grullon et al. (2002), and earned to contributed capital ratio by DeAngelo et al. (2006), to gain intuition about the different information they are capturing. In Appendix B, I run a logistic regression with the individual strategic groups as the dependent variable and other life cycle measures as independent variables. The pseudo R-squared for the regressions reaches up to 0.05 (0.10 with industry and year fixed effects), implying that most of the measure's variation is left unexplained by the current proxies. The coefficient for age is the highest for stuck-in-the-middle companies, while the coefficients for the earned-to-contributed capital ratio and assets are close to zero. Thus, the strategy proxy provides different information not incorporated in the current life cycle proxies.

Table 5 presents the example of Amazon.com from 1997 to 2017. Arikan and Stulz (2016) age proxy contains 3 phases: young, middle-aged, and mature companies. As Amazon had its initial public offering in May 1997, this proxy pegs Amazon as a young company from 1997 to 1999, middle-aged between 2000 and 2005, and mature company from 2006. On the contrary, Column 2 demonstrates that Amazon so far never issued dividends; therefore, it never increased dividends. The absence of dividends suggests that the Grullon et al. (2002) maturity hypothesis, which contends that the increase in dividend payment indicates companies' maturity, would not categorize Amazon during that period as a mature company. Nevertheless, the average earned to contributed capital ratio is negative before 2008 and positive afterward, linking Amazon to the high-growth and mature stages. Lastly, the strategy proxy marks Amazon as a performance-maximizing or sales-maximizing company in that period.

[Insert Table 5 about Here]

The table also displays further distinctions between the proxies. The age proxy permits only young-middle aged-mature firm life cycle path, and companies cannot relocate to the preceding stages. Dividends and retained earnings rely on the dividend life cycle hypothesis, and they can separate only between mature and non-mature companies. Conversely, the new measure can distinguish between the four strategies, and movement among them is not predetermined, nor do companies have to apply different strategies over the years. For instance, Amazon repositions from a performance-maximizing to a sales-maximizing company and vice versa. According to the transition matrices in Table 4, a company can preserve the same position, or it can evolve to one of the three remaining strategies in any period.

To mitigate concerns that Amazon might be a company with rare discrepancies, I calculate the percentage of classifications that diverge between the age proxy and the strategy proxy on the entire sample of companies. I use two diverse but conservative estimates as the number of stages differs among the two proxies (three versus four). The first estimate perceives a difference between the two proxies only if: 1) the strategy proxy groups a firm into a performance-maximizing, while age proxy detects the firm as old; 2) the strategy proxy labels a firm as stuck-in-the-middle, and age proxy tags it as the young phase. The percentage of differently categorized companies is a ratio between firm-year observations that fit in one of the two groups and the total number of observations in the sample. The calculation reveals that 12% of the company-year observations are binned to the opposite stages. The second estimate appends two additional categories: performance-maximizing and stuck-in-the-middle firms by the strategy proxy that correspond to the middle group in the age proxy. It suggests that 30% of the firms would not belong to a similar strategy according to the two proxies. Overall, company's strategy provides information not fully embodied by the traditional life cycle proxies.

5 Results

Competitive strategy governs how companies allocate scarce resources to create a competitive advantage, with the ultimate goal of maximizing firms' values. Therefore, it has a direct bearing on firms' investment decisions. In the first step, I analyze this hypothesis; if companies take into account their competitive strategy in acquisition decisions, companies' strategies should affect the probability of becoming an acquirer. The second step studies whether acquirers consider target firms' strategies by exploring how competitive strategy impacts the probability of becoming a target company. The third step investigates the acquirers and the target strategic pairs to understand whether acquirers select targets that match their strategies or all acquirers focus on the targets with one strategy type. These three steps provide a base to examine the strategic similarity hypothesis.

The strategic similarity hypothesis states that M&A deals in which the acquirer and the target firm embrace the same strategy outperform other deals (Lubatkin, 1983; Ramaswamy, 1997). The driving mechanism is that the divergence between the strategic approaches in M&A deals acts as a constraint to a company's optimal response to business and investment opportunities, leading to worse performance. The results in line with the theory's predictions should pinpoint that acquirers seek out targets with the same strategy and that those deals reap higher synergies.

Furthermore, if the delays in the investment decisions represent the underlying mechanism, I expect the effect to be stronger in a high-competition environment compared to a low-competition environment, as the timely reactions to business threats and opportunities are more important with intense competition (Makadok, 1998; Christie et al., 2003). Also, success in different industries depends on different requirements, which lessens the necessary strategic fit in diversifying acquisitions (Ramaswamy, 1997). On this ground, I study the deal performance of the same strategy deals and the likelihood of acquiring a company with the same strategy in low and high-competition environments and in related and diversifying deals.

5.1 Acquirers' strategies

I begin by inspecting the acquirers' strategic traits. Figure 2 illustrates the ratio of acquirers' strategies over the years. Acquirers do not cluster in one strategic group but spread through all the groups. The result implies that companies continuously evaluate also external investment opportunities and they do not have to necessarily exhaust their internal projects before acquiring other companies. Compared to all the companies in Figure 1, sales-maximizing companies reach a higher percentage.

[Insert Figure 2 about Here]

For a direct test, I run a conditional logistic regression, following Bena and Li (2014) for acquirer 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 acquired another public company or a subsidiary in a given year, and zero otherwise. Since a company fits only one of the four strategies, the cost-minimizing group acts as the reference category[12], and the coefficients should be interpreted in relation to the cost-minimizing group. X is a set of control variables: assets, age, debt, MB ratio, profitability, and R&D costs, which have been shown in previous studies to predict a firm's probability of becoming a target or an acquirer firm. η are the deal fixed effects. 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 6 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 have the most similar propensity-matching score based on assets, age, debt, MB ratio, and profitability.

Table 6 Columns 1 and 2 report the coefficient estimates. The columns imply that cost-minimizing companies have the lowest probability of becoming acquirers. After considering other explanatory variables in Column 4, sales-maximizing and performance-maximizing companies are associated with the highest probability of becoming acquirers. Considering the control variables, the odds of becoming an acquirer for the performance-maximizing (sales-maximizing) companies are 1.59 (1.57) times as large as the odds for the cost-minimizing companies. Smaller size, older, lower debt ratio, lower profitability, lower MB ratio, and higher R&D compared with the closest

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

companies by propensity matching score positively affect the likelihood of becoming an acquirer. In summary, this section substantiates that acquirers choose different competitive strategies, which hints that they should also aim for different target firms.

5.2 Target firms' strategies

The paper is articulated around the idea that acquirers consider targets' competitive strategies in their M&A decisions. To test this hypothesis, Figure 3 plots the fraction of the target firms in distinct strategic groups over the years. Targets are located in all the groups, but compared with all the companies in Figure 1, stuck-in-the-middle and performance-maximizing companies capture a larger share with the maximum of 31% and 37%, respectively (compared with 20% and 34% in the whole sample of companies in Figure 1).

[Insert Figure 3 about Here]

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

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

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 6 Columns 3 and 4 record coefficient estimates from the conditional logit regression. Across specifications, stuck-in-the-middle and performance-maximizing companies are associated with a higher probability of becoming targets, significant at the 1% level. For the performance-maximizing (stuck-in-the-middle) companies, the odds of becoming a target are 1.62 (1.37) times as large as the odds for companies pursuing the cost-minimizing strategy. The results support the hypothesis that the target firm's strategy shapes the acquiring firm's focus of the search, and it rules out that the bulk of target firms hoards in one strategy (for example, the performance-maximizing strategy). Compared with the closest firms by the propensity score, smaller size, older, higher profitability, lower debt, and higher R&D companies are positively related to the probability of becoming a target.

5.3 Strategic pairs

After demonstrating that both acquirers' and targets' strategies matter in M&A deals, the next step analyzes the acquirer-target pairs. Table 7 partitions the deals on the acquirer and target strategy 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 strategy; the percentage varies from 30% for stuck-in-the-middle firms to 48% for performance-maximizing firms. Table 8 presents deal examples for each acquirer-target strategy pair.

[Insert Table 7 about Here]

[Insert Table 8 about Here]

As the number of companies in different strategies does not have to equate, I investigate this pattern in a more formal setting. Table 9 shows coefficient estimates from the conditional logit regression for acquirer i, target j, deal m, and year t:

$$RealPair_{i,j,m,t} = \alpha + \beta SameStrategy_{i,j,t-1} + \delta_1 X_{i,t-1} + \delta_2 X_{j,t-1} + \eta_m + \epsilon_{i,j,m,t}, \tag{3}$$

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 industry and the same year, as in Table 6. The coefficient of interest is related to *SameStrategy*, a dummy variable equal to one if a company pair overlaps in the strategy and zero otherwise. Table 9 Column 1 includes only the variable *SameStrategy* and Column 2 saturates the model with control variables.

[Insert Table 9 about Here]

In both columns, *SameStrategy* exhibits a positive and significant coefficient at the 1% level, indicating the same strategy leads to merger pairing. For the companies that pursue the same strategy, the odds of a transaction are two times as large as the odds for companies that belong to different groups. The other control variables show predictable signs. The findings are also in line with Chen et al. (2020a). Using firm IP addresses to track downloads of financial statements from Bernard et al. (2020), they document that firms download more information about the companies in the same life cycle, especially before and during an acquisition process. Table 9 lends strong support for the strategic synergies: acquirers select targets that match their strategic needs.

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

5.4 Ex-post outcomes

I examine the benefits of the same strategy deals through financial and real ex-post outcomes. Table 10 tests the financial outcomes by estimating combined acquirer and target announcement return for acquirer i, target j, acquirer's industry z, year t:

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

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 10 about Here]

I implement the Carhart 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 120-day period, from event day -130 to event day -11, as suggested in Campbell et al. (1997). Combined returns are weighted by their 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 (2019)).

Table 10 Column 1 includes only the variable of interest *SameStrategy*, 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 *SameStrategy* 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 strategic group yield, on average, 87 basis points higher combined announcement returns compared with the pairs with different stages. Control variables exhibit predictable signs. Thus, the combined return analysis authenticates the strategic synergies.

Next, I track whether the financial value creation of acquiring a company with the same strategy is accompanied by real post-acquisition gains, particularly asset and sales growth. The challenge is that asset and sales growth may be endogenously related 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) strategy with the firms that acquired a target company with the same (different) strategy. 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 strategy data, the procedure results in 801 withdrawn acquisitions. The withdrawn acquisitions occur during the same year as the matched effective acquisitions, and acquirers of the two acquisitions have the same age.[13] 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 strategy, and 192 pairs with a different strategy. 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 4 verifies the parallel trend assumption for assets, and Appendix C focuses on the parallel trend in sales. Panel A in Figure 4 plots the average asset size for the treatment and control

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

subsample for the deals with the same strategy, while Panel B plots the deals where the acquirer and the target have different strategies. 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 this 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 strategy experience a stronger asset growth than their control sample. In contrast, companies that acquired a target with a different strategy 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 4 about Here]

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

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

The dependent variable, $Assets_{i,j,t}$, is the acquirer's assets of the deal i, j at time t.[14] 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 11 Columns 1 and 2 display coefficient estimates from the OLS regression in Equation 5 using a subsample of deals with and without strategy overlap. The coefficient on the interaction term *After**Effective* is positive and significant at the 1% level for deals with the strategic overlap, while negative and significant at the 5% level for deals without the strategic overlap. Completing a deal between firms with the same strategy generates asset growth, while buying a target with a different strategy results in lower assets.

[Insert Table 11 about Here]

[14] The dependent variable in Appendix C is $Sales_{i,j,t}$, the acquirer's sales of the deal i, j.

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

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

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 *SameStrategy* equals one for the deals in which the acquirer and the target have the same strategy and zero otherwise. The coefficient of interest is β_4 for the interaction term between *SameStrategy*, *After*, and *Effective*, which detects the effect on asset size of acquiring a target with the same strategy.

Table 11 Column 3 presents coefficient estimates from the OLS regression in Equation 6. The coefficient on the interaction term *SameStrategy*After* is negative and significant at the 5% level. But this decline is reversed for the companies that acquire targets with the same strategy; the coefficient on the triple interaction term *SameStrategy*After*Effective* is positive and significant at the 1% level. The interaction term is also positive and significant at the 1% level in Appendix C Column 3.[15] The findings establish that the strategic synergies deliver real post-acquisition gains, supporting the predictions of the theory.

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 11 Column 4 displays the estimates. The coefficient on the interaction term *SameStrategy*After*Effective* is statistically indistinguishable from zero, certifying that the captured asset growth emanates from acquiring the company with the same strategy. The findings are the same for sales in Appendix C. The results in this section highlight that companies consider the target firm's strategy as an important factor in M&A deals because of the financial and real benefits emerging from the strategic similarity.

[15] Eliminating the acquisition pairs without all 7 years (3 years before the announcement, the announcement year, and 3 years after the acquisition) shrinks the sample to 7302 observations, with 5273 observations with the same strategy and 2029 observations with a different strategy. 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 strategic similarity hypothesis postulates that companies opt for a target with the same strategy because this selection leads to faster 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, the theory suggests that selecting a target firm with the same strategy is 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 is a measure of 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 12 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 9. The coefficients on $SameStrategy$ are all positive and statistically significant at the 1% level, indicating that companies, in general, prefer targets with the same strategy. However, positive and highly statistically significant interaction terms $SameStrategy * HighCompetition$ and $SameStrategy * HighFluidity$ show that the effect is more pronounced with vigorous competition. This result validates the prediction that decreasing collaborative frictions play an especially vital role with intense competition.

[Insert Table 12 about Here]

Second, the theory assumes that strategic differences between a target and a bidder in different industries might not be detrimental, as the requirements for success vary between the industries (Ramaswamy, 1997). Therefore, I test whether the negative impact of strategic dissimilarity is stronger in the same industry mergers compared to diversifying acquisitions. Table 12 Columns 5 and 6 present the conditional logistic regression results in Equation 3 using the interaction term between the $SameStrategy$ and $SameIndustry$ variables. $SameIndustry$ is an indicator variable equal to one if two companies operate in the same industry, as in Chen et al. (2020b). Column 5 does not include any control variables, while Column 6 implements the full set of control variables. The coefficient on $SameStrategy * SameIndustry$ is positive and statistically significant at the 1% level in both the columns, implying that the strategic similarity is more important in the same industry deals, consistent with the theory. The result substantiates that strategic dissimilarity acts as a constraint to the merged company's timely 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.

Table 13 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 *SameStrategy* is still positive and highly statistically significant. I also substantiate that product similarity alters the pairing decisions. Table 13 Column 2 further incorporates broad similarity and product similarity for targets as independent variables. 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 strategy. 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 strategically similar with little market overlap, but also strategically different with substantial market overlap.

[Insert Table 13 about Here]

Bena and Li (2014) proclaim that the presence of technological overlap 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. Table 13 Column 3 mimics the conditional logit regression in Equation 2 with the 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. Strategy and technological synergies disclose positive and highly statistically significant coefficients. Column 4 displays that the strategy variable's 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. I follow the authors and define culture 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 13 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 same strategy coefficient is positive and statistically significant at the 1% level, suggesting that corporate culture does not fully explain the strategy variable. 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 strategic similarity represents a strong factor affecting M&A deals.

7 Conclusion

This paper provides evidence of competitive strategies' impact on firms' investment decisions. It shows that firms consider their own and their target firm's competitive strategy in M&A deals. Buying a target company with the same strategy 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 the merged companies whose acquirers and target firms apply the same strategy can react faster to investment opportunities and market threats. Overall, the results emphasize the importance of the firm competitive strategy in investment decisions.

The paper also makes a methodological contribution. I propose a relative proxy to estimate competitive strategy, 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, for example, all companies in a high-tech industry are not classified as performance-maximizing, and all companies in the oil extraction industry are not flagged as cost-minimizing. Instead, each industry can have companies applying different strategies.

One limitation of this study lies in the implicit assumption of the relative measure that each industry contains companies across all the strategic groups. Thus, the relative measure does not reveal the strategy of an industry or companies' tendency to transition toward a specific strategy within a particular industry over the years. The second limitation refers to the sample; it is restricted by the availability of 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. Also, the analysis could be extended to other related questions, like serial acquirers' strategy and their targets.

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Figure 1: Firm strategies over years

The figure shows the fractions of US firms' strategies between 1994 and 2017. The solid line represents firms applying the performance-maximizing strategy, the dashed line shows firms applying the cost-minimizing strategy, 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 strategies is described in Section 4 and Appendix A.

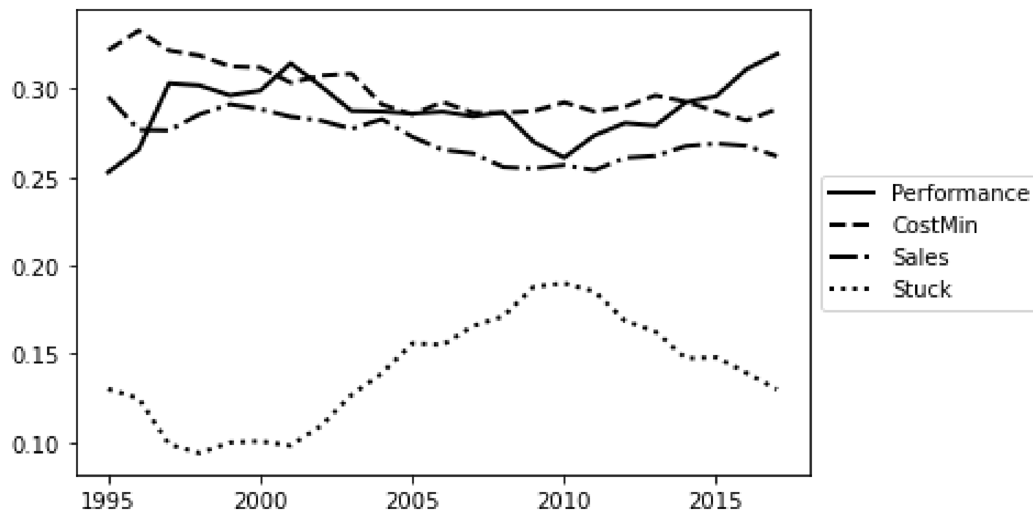


Figure 2: Acquirer strategies over years

The figure shows the fractions of US acquirers' strategies between 1995 and 2017. The solid line represents firms applying the performance-maximizing strategy, the dashed line shows firms applying the cost-minimizing strategy, 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 strategies is described in Section 4 and Appendix A.

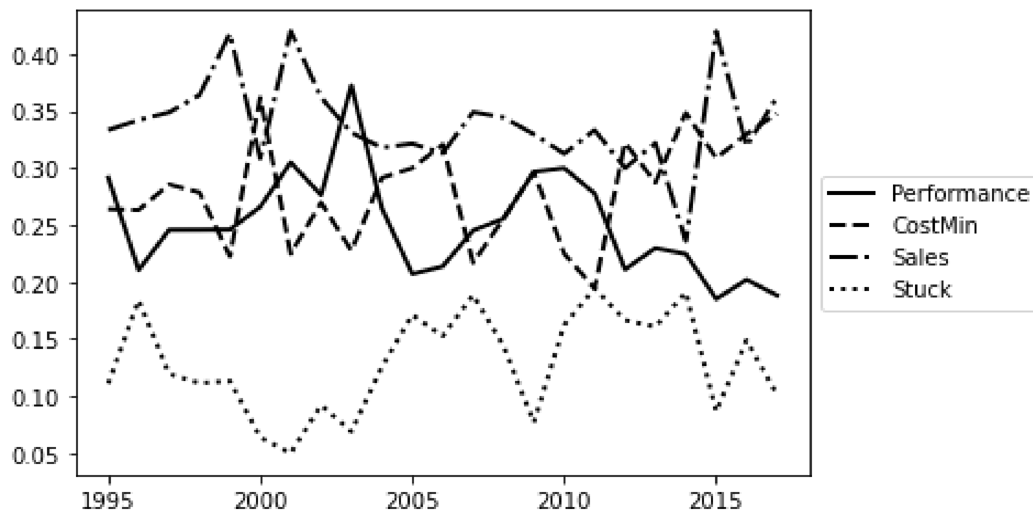


Figure 3: Target firms' strategies over years

The figure shows the fractions of US target firms' strategies between 1995 and 2017. The solid line represents firms applying the performance-maximizing strategy, the dashed line shows firms applying the cost-minimizing strategy, 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 strategies is described in Section 4 and Appendix A.

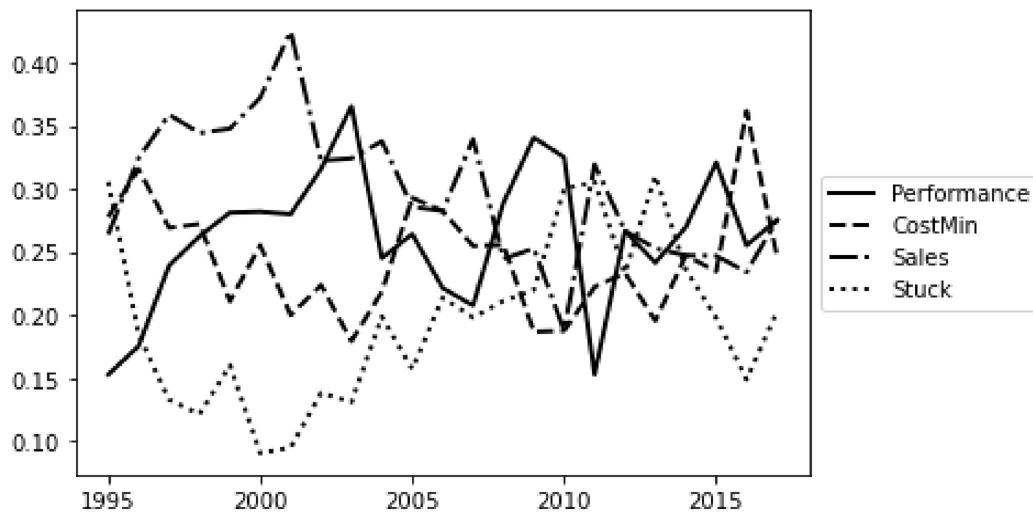


Figure 4: Asset size of acquirers and companies that withdrew their bid

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 strategy, while Panel B displays the deals with the acquirer and the target with different strategies. The gray area on the graph marks the announcement year.

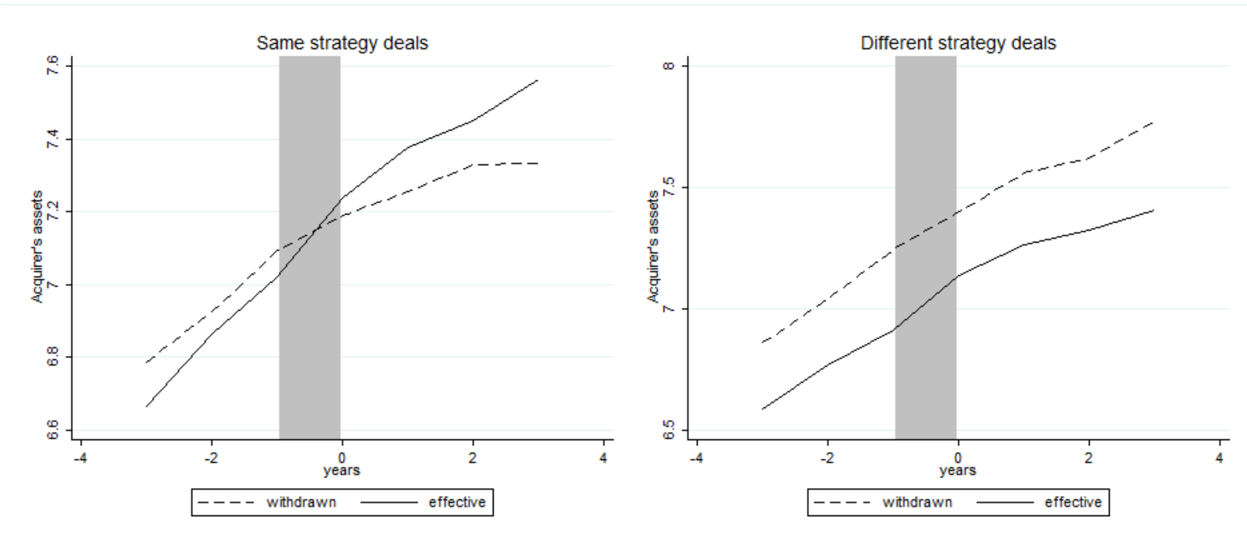


Table 1: Public corporate acquisitions over time, 1995-2017

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
Strategy	2.34	0.99	1.00	2.00	3.00
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
Strategy	2.40	1.06	1.00	2.00	3.00

Table 3: Average firm characteristics by strategy 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 strategy 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
CostMin	11.04	1.17	2.29	0.18	0.25	0.01	4.19	0.17	0.58	0.21	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
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 strategies for US public firms during the period 1994-2017.The detailed explanation of the firm strategy is given in Section 4.

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

Table 5: Differences between different life-cycle proxies for Amazon

The table shows the differences between different life-cycle proxies and the competitive strategy proxy for Amazon between 1997 and 2017. The detailed explanation of the firm strategy is given in Section 4. Age is number of years since the IPO. Retained earnings is earned to contributed capital ratio, calculated as retained earnings over assets. Dividends are dividends payed.

Year	Strategy	Age	Retained earnings	Dividends
1997	1(Performance-max)	1(young)	-.226	0
1998	1(Performance-max)	2(young)	-.247	0
1999	1(Performance-max)	3(young)	-.358	0
2000	1(Performance-max)	4(middle-aged)	-1.075	0
2001	1(Performance-max)	5(middle-aged)	-1.769	0
2002	1(Performance-max)	6(middle-aged)	-1.507	0
2003	1(Performance-max)	7(middle-aged)	-1.358	0
2004	3(Sales-maximizing)	8(middle-aged)	-.725	0
2005	3(Sales-maximizing)	9(middle-aged)	-.547	0
2006	3(Sales-maximizing)	10(old)	-.421	0
2007	3(Sales-maximizing)	11(old)	-.211	0
2008	3(Sales-maximizing)	12(old)	-.103	0
2009	3(Sales-maximizing)	13(old)	.008	0
2010	3(Sales-maximizing)	14(old)	.060	0
2011	3(Sales-maximizing)	15(old)	.065	0
2012	1(Performance-max)	16(old)	.051	0
2013	1(Performance-max)	17(old)	.050	0
2014	1(Performance-max)	18(old)	.026	0
2015	3(Sales-maximizing)	19(old)	.028	0
2016	3(Sales-maximizing)	20(old)	.047	0
2017	3(Sales-maximizing)	21(old)	.062	0

Table 6: 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 became 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. 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) Target	(4) Target
Performance-max	0.462***	0.452***	1.143***	0.481***
	(0.053)	(0.074)	(0.059)	(0.079)
Sales-max	0.084*	0.435***	0.257***	0.166***
	(0.049)	(0.059)	(0.053)	(0.060)
Stuck	0.209***	0.163**	0.417***	0.315***
	(0.069)	(0.076)	(0.068)	(0.079)
Assets		-0.533***		-0.724***
		(0.020)		(0.023)
Age		0.140***		0.123***
		(0.009)		(0.010)
MB		-0.079***		0.007
		(0.018)		(0.015)
EBITDA		-11.436***		0.862***
		(0.632)		(0.105)
Debt		-1.586***		-2.789***
		(0.139)		(0.152)
R&D		2.320***		0.431**
		(0.551)		(0.175)
Deal FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.01	0.33	0.04	0.39
Observations	18620	18620	18621	18621

Table 7: Acquirer-target strategy pairs

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

	Targets' strategy				
Acquirers' strategy	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 8: Example deals of mergers and acquisitions in each acquirer-target strategic group

The detailed explanation of the competitive strategy measure is given in Section 4.

Acquiror strategy	Target strategy	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 9: 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 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)
	RealPair	RealPair
SameStrategy	0.703***	0.697***
	(0.041)	(0.044)
Assets_acq		-0.443***
		(0.018)
Age_acq		0.108***
		(0.008)
MB_acq		-0.059***
		(0.015)
EBITDA_acq		-8.730***
		(0.581)
Debt_acq		-1.312***
		(0.125)
R&D_acq		3.371***
		(0.534)
Assets_tar		-0.572***
		(0.019)
Age_tar		0.107***
		(0.008)
MB_tar		0.019

		(0.013)
EBITDA_tar		0.523***
		(0.089)
Debt_tar		-2.264***
		(0.127)
R&D_tar		0.909***
		(0.172)
Pseudo R^2	0.02	0.26
Observations	34137	34137

Table 10: 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 their market capitalization of both participants 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
SameStrategy	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 11: 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 *SameStrategy* 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 ×. 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)	(2)	(3)	(4)
	Assets	Assets	Assets	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)
SameStrategy × After			-0.208**	-0.010
			(0.082)	(0.094)
SameStrategy × 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 12: 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
SameStrategy	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)				
SameStrategy × HighCompetition	0.232***	0.179*				
	(0.084)	(0.096)				
HighFluidity			-0.076*	-0.058		
			(0.045)	(0.064)		
SameStrategy × HighFluidity			0.441***	0.364***		
			(0.084)	(0.096)		
SameStrategy × 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 13: 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)	(2)	(3)	(4)	(5)
	RealPair	RealPair	RealPair	RealPair	RealPair
SameStrategy	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 A

Following Hoberg and Maksimovic (2019), 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

B Appendix B

Relation between strategy and life-cycle

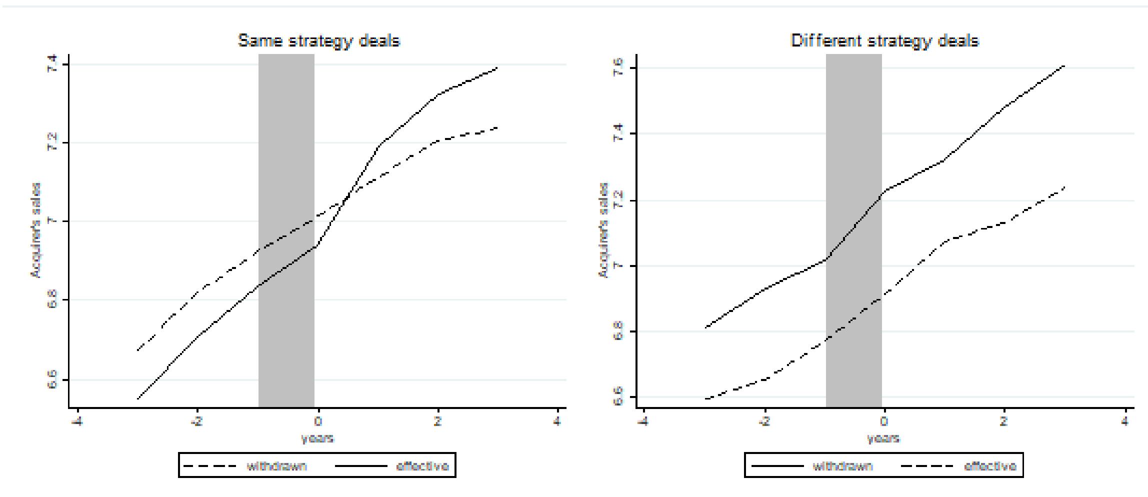
The table shows the coefficient estimates from logit model, where the dependent variable $Perf$ in the first four columns is a dummy variable equal to one if a company belongs to the performance-maximizing group in a given year. The dependent variable in Columns 5 to 8 is $CostMin$, a dummy variable equal to one if a company belongs to the cost-minimizing group in a given year. 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. 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. 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
Pseudo R^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

C Appendix C

Sales of acquirers and companies that withdrew their bid in the same strategy deals and different strategy 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 strategy, while Panel B displays the deals with non-overlapping strategies. Year 0 is the year of the announcement.



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 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 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 *SameStrategy* 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 $\times$. 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 $\times$ Effective	0.052	-0.250***	-0.248***	-0.141
	(0.049)	(0.083)	(0.083)	(0.101)
SameStrategy $\times$ After			-0.172**	0.113
			(0.081)	(0.095)
SameStrategy $\times$ After $\times$ 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